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ÖSTERREICHISCHES INSTITUT FÜR WIRTSCHAFTSFORSCHUNG

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## Abstract

The aim of this study is to analyse the development of new industrial specialisations and the process of export diversification both at the country and the regional level for the EU countries over time. It examines to what extent these processes show path dependent properties, whether persistent development trajectories can be shifted in order to avoid structural traps and what role related and unrelated diversification play for the economic performance of regions. Overall, the results of this report and its policy implications underscore that Smart Specialisation policies require a smooth coordination of a larger set of diverse policy measures that take into account both the local context and all the involved players rather than a perfect setup of single policies. In particular, the educational system, specialisation patterns in research and innovation, and foreign direct investments play a key role in diversification processes and should be a constitutive element of Smart Specialisation policies.

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# EXECUTIVE SUMMARY

The ***aim of this study*** is to analyse the development of new industrial specialisations and the process of export diversification both at the country and the regional level for the EU Member States over time. It examines to what extent these processes show path dependent properties, whether persistent development trajectories can be shifted in order to avoid structural traps and what role related and unrelated diversification play for the economic performance of regions. Finally, the report derives policy conclusions for Smart Specialisation policies in the EU.

***Smart Specialisation Strategies (3S)*** have become the primary policy-prioritization logic in recent efforts by the European Union to promote economic development and growth of European regions. They are an essential element in important domains of EU policy making such as EU Cohesion Policy and have been emphasised in a number of initiatives. Over the past years, Smart specialisation strategies (3S) have therefore evolved into a key policy approach to achieve the goals set out in its *Europe 2020 strategy*. They are seen as a means to promote Europe's competitiveness both at the national and the regional levels through the development of unique specialisations and the exploitation of diversification potentials. The ultimate goal is to close the productivity gap relative to the US, and maintain or even increase the distance to other emerging industrial nations, as well as support ecologically and socially sustainable development in Europe.

Smart Specialisation Strategies target the capacity of a country or region to develop new economic activities and generate growth enhancing structural change. The central idea is to ***promote the diversification around a core set of activities and themes that draw on the existing local knowledge base with the aim to develop it further by deepening and broadening*** it. Smart Specialisation Strategies put in place a process whereby diversification into new (and related) economic activities is facilitated thanks to targeted public R&D support fostering entrepreneurial search and discovery in promising new activities that on the one hand can benefit from local capabilities and knowledge spillovers while broadening at the same time the local knowledge base. As such this approach is distinct from classical specialisation policies, like early cluster approaches, that typically tend to support already existing areas of strength and encouraging sectoral specialisation which amounts to a narrowing down of the variety of economic activities.

The novelty of the Smart Specialisation approach to industrial and regional policy is that it does away with horizontal approaches to industrial and regional policy that have proven ineffective in the past, and puts ***the local development context at the centre stage*** of policy making. Smart Specialisation explicitly recognises that economic development both at the national and the regional levels is highly dependent on specific local capabilities that have accumulated over time and that heavily depend on and co-evolve with untraded technological interdependencies and information flows, common infrastructures as well as economic, technical or educational institutions. This implies that there is ***no one-size-fits-all solution*** to promote economic development and structural change in EU Member States and their regions. It is necessary to take into account the ***heterogeneity of countries and regions*** in the development and design of industrial and regional policies. For this to be effective, Smart Specialisation policies require a careful analysis of regional or national specialisation patterns and the underlying knowledge capabilities, research competencies and industry structures.

The ***key ingredients of Smart Specialisation Strategies (3S)*** are on the one hand the identification of areas of strengths and on the other hand the identification of potential avenues to diversify them into new, related domains with high market potential and to support structural adjustments towards these areas. In order to properly understand this approach and make it amenable to empirical analysis some definitions are needed and a number of questions have to be answered. Firstly, the notion of "***areas of strength***" has to be defined. Secondly, it is necessary to understand ***which factors influence these areas of strength***. Thirdly, it is important to understand also the ***determinants of diversification processes***. Policy conclusions can only be drawn if these aspects have been defined and analysed.

The report tackles these questions with a comprehensive econometric analysis of the ***importance of related capabilities and product sophistication on specialisation patterns and economic performance***. It furthermore investigates ***how countries or regions might overcome path dependency*** in their industry structures. Although the analyses take different perspectives at different levels of aggregation using a broad range of various datasets and indicators the findings robustly show a consistent picture. This is plausible as the main indicators used in the analyses are highly disaggregated. The unit of observation are 6-digit product classes (following the HS2002 classification) for analyses at the country level and 4-digit industries (NACE Rev. 2) at the regional level. Hence, the main advantage of this study is based on linking highly disaggregated information to the national and regional institutional context.

The entire ***report focuses on the manufacturing sector***. This is largely predetermined by the type of data used and not by an implicit prioritisation of manufacturing over other economic sectors in this study. Indeed, services, such as tourism, or complementarities between business services and manufacturing can be and often are an important source of competitiveness and economic prosperity especially at regional levels. However, the data and methods used in this report do not allow analysing these aspects directly. Nevertheless, this does not significantly limit the validity of the results. Rather it is also important to highlight, as the European Commission has underscored in recent communications on industrial policy, that ***manufacturing is an important source of wealth, income and prosperity in Europe*** and as such it should be given particular attention.

Chapter 2 of this report examines the *relationship between international competitiveness, local capabilities and untraded technological interdependencies*. The analysis explicitly takes into account that competitiveness is the outcome of a process of competition in which market and demand conditions play an important role. The results indicate the strong interdependence and importance of technological interdependencies at the country level in explaining competitiveness. This chapter also identifies areas where new comparative advantages could emerge across countries, sectors and technology fields taking into account the most important determinants of international competitiveness. Country fiches detailing these results for each EU member state are included as an extended appendix to this report.

The purpose of chapters 3 and 4 is to analyse the *relationship between national capabilities to generate and apply knowledge and the development of comparative advantages and changes in industrial specialisation* at the national and regional level respectively. The chapters provide an econometric analysis of the relationship between specialization, diversification and competitiveness on the one hand and capabilities to generate and absorb knowledge at the other hand. In particular, the chapters focus on the role of education and skills, innovation activities (measured in terms of patent applications) and knowledge inflows from FDI and capital goods imports to foster diversification and overcoming path dependencies.

The results robustly confirm patterns of path dependency resulting from the local development context. Moreover, the empirical evidence found also suggests that ***new comparative advantages*** in trade and export potentials are likely to ***emerge in activities that are related to existing areas of strengths***. It also supports arguments in favour of public intervention to boost diversification processes as it indicates that the underlying technological search is indeed fairly close to existing core-capabilities of the business sector of an economy. Firms typically focus their economic activities and research and innovation efforts around their main fields of activity which reinforces existing specialisation patterns. If policy does not act to increase the variety of economic and knowledge generating activities, this may lead to structural traps of development, i.e. specialisations that at some point in time come under competitive pressure but that are difficult to leave due to change.

From a policy point of view it is therefore an important question how to widen specialisation patterns and ensure that comparative advantages can also be achieved in products and industries that draw on knowledge bases that are technologically distant but still related to the established fields of strength of a country or region. The empirical findings presented in chapters 3 and 4 clearly show that ***educational investments may weaken path dependency*** reducing the importance of already existing local capabilities and ***allowing to tap into new technologies or industries fostering diversification***. Furthermore, better educated countries are in general more specialised in high-end niche markets. More sophisticated products involve more complex activities and therefore a larger number of technological competencies to draw upon. While this is a well known outcome, it clearly shows that there are limits to diversification for a given level of technological capabilities in a country. Indeed, countries that are closer to the technological frontier are typically also more competitive and specialised in more sophisticated products. ***Building up the capabilities to develop and produce such products depends heavily upon a combination of protracted government investment in the knowledge base*** of a country or region, ***and business allocation of resources to innovative investment strategies***. The collective and cumulative character of learning processes makes it therefore difficult for regions or countries that are farther off the technological frontier to succeed in attempts to diversify into industries requiring complex technological capabilities. Rather, the results suggest that they have to pursue the strategy to diversify into more sophisticated products in established industries, and move into more complex activities gradually as they accumulate technological capabilities over time. Leapfrogging from productive structures with low levels of technological sophistication into productive structures with high levels of sophistication is therefore unlikely without sustained investments into education, knowledge absorption and knowledge creation. It is all the more difficult for activities in technological fields where tacit knowledge plays an important role.

The ***educational system*** therefore plays a key role in diversification processes and ***should be a constitutive element of Smart Specialisation Policies***. Educational systems should not only be linked to the labour demand of firms located in the country or region but also adapt flexible to changing requirements over time, i.e. striving to match skill profiles (i.e. labour supply) to the (future) demand for skills. However, Smart Specialisation policies have also to solve the ***trade-off between providing highly specialised skills and high-quality general education***. If educational activities are too focused on the needs of the business sectors, too little new knowledge from other domains will flow into the system with the effect that the variance of knowledge and skills levels among economic activities becomes too small which can reinforce structural traps. In the context of tertiary education it is important to strike the balance between developing and supporting a system of advanced technical colleges linking up their educational and research agendas to business needs especially in a regional context and supporting general universities that should provide high level general education by linking up to leading edge science.

Moreover, it is a long-standing belief among policy makers and scholars that inward FDI is one of the most important channels through which foreign technology, management skills and production know-how diffuses in an economy and contributes to domestic long-run growth. However, the existing evidence on the impact of inward FDI on the domestic knowledge base is mixed and the potential impact of inward FDI on the domestic knowledge base is ambiguous. The empirical findings presented in chapters 3 and 4 show very heterogeneous effects of inward FDI on comparative and competitive advantages as well as industrial specialization patterns both at the country and the regional level. ***While inward FDI could potentially contribute to diversification it tends to deepen existing specialisations*** because foreign owned firms seem to be more interested in exploiting local knowledge and related externalities to their own benefit. For profit maximising companies this is a quite natural strategy to pursue. Nevertheless, the results indicate that inward *FDI can indeed contribute to strengthen existing comparative and competitive advantages.* ***Whether these effects materialise will depend on how well foreign owned companies can draw on existing local capabilities and contribute to them and hence on their embeddedness in the local productive system***. If countries fail to embed foreign owned companies that are active in areas that are weakly related to the established production and innovation systems they are likely to lose these companies again in the medium-term. The measures needed to embed foreign owned companies in the local production and innovation ecology will differ across regions, but generally they should try to ***support foreign owned firms to develop complementarities between the companies own capabilities and the supply and generation of local capabilities and production factors***.

The empirical findings in chapters 3 and 4 furthermore show that ***local technological search and knowledge generation reinforce existing specialisation patterns*** since companies have an incentive to engage into research and innovation activities that are closely related to their core competencies. However, industries that patent in technological fields closely related to the local knowledge base have also comparative advantages relative to other industries where this is not the case. However, the results also suggest that local technological search may eventually weaken comparative advantages if it is too narrowly focused. This finding lends support for public intervention through targeted R&D support. The ***aim of this targeted R&D support should be to promote the renewal of established economic activities as well as innovation and diversification into products or technologies that are related to established competences***. In this way they should support the emergence of new activities that are rooted in the productive system of a country (or region). It should encourage recombination of established competences with new ones and ensure that activities of knowledge/technology creation and technology diffusion are well embedded in local productive and innovation systems. Recombination of capabilities can happen through a number of channels. The most important policy options are:

1 Mission oriented policies,

2 policies supporting entrepreneurship, discovery and recombinant technical change in industries, and

3 research and technology policies targeting relatedness and recombination.

These broadly defined fields of action are interdependent and have all taken by themselves a number of strengths and weaknesses. ***Mission oriented policies in the context of Smart Specialisation strategies should explicitly take into account local capabilities***. One potential danger is that the goals set out by the mission rely too heavily on undeveloped capabilities (e.g. new principles of operation or materials) or on capabilities that are not related to existing capabilities. In this case it is likely that the mission fails. On the other hand, scientific research often identifies opportunities from its own results that prime commercial application. Therefore there is a major reason for being concerned with the diversity of the research and the scientific portfolio, especially in the context of mission orientation. The ***policy design therefore has to find the right balance between mission driven diversification relying on related technologies and mission driven diversification relying on weakly or unrelated technologies***. In the design of mission oriented programmes it is necessary to define goals broadly, while ensuring bottom up research on related problems both from a broad scientific and from more narrow technological and engineering perspectives. This is all the more important to avoid that mission orientation promotes technological lock-in.

***Established research and technology policies could also be modified to that they are better able to target relatedness and recombination***. Non-mission oriented bottom up type of research funding measures and programmes could target related and recombinant technical change more accurately through specifically designed award mechanisms favouring R&D projects targeting recombinant technical change and diversification over incremental technical change. While in practice it seems probable that it would be difficult to work out general principles of funding that would be able to take diversification processes fully into account, substantial knowledge on the patterns of technical change nowadays is available and should be used to design research funding. As recombinant technical change is a key ingredient of related diversification knowledge on this type of technical change should be used in the context of Smart Specialisation approaches.

In order to ***avoid "picking the winners"*** approaches a "Smart Specialisation" policy should ***support entrepreneurship and entrepreneurial discovery***. The emphasis should lie on innovation activities that aim recombining competences across technological fields and sectors. Such processes are typically supported by a number of knowledge transfer mechanisms, in particular labour mobility, entrepreneurial activities through spin-offs, and the design of award mechanisms for R&D support programmes.

Chapter 5 complements the analyses by examining the effect of specialisation and diversification patterns on regional economic performance. In theory both relatedness and diversity of production structures and knowledge bases matter for regional economic performance, but their relative importance may differ by region type and economic circumstances. The first key result of the empirical analysis is that the employment effects of related and unrelated variety differ by regional distance to the frontier. On the one hand, ***related diversification matters for regions at or close to the technological frontier***, which are predominantly technologically advanced and industrially mature regions from the EU-15, where industry-specific knowledge spillovers generate the most employment gains. On the other hand, ***regions further away from the frontier generate employment growth through unrelated diversification***. These are mostly regions from the EU-13 that tend to be characterised by earlier stages of industrial and technological development and are thus more likely to gain from knowledge spillovers from unrelated industries. Structural change and FDI inflows since economic transition have also given rise to less related local production structures in these regions.

The second key result emerging from the analysis of economic performance is that unrelated variety in production was the main driver of aggregate regional employment growth between 2008 and 2011. In addition, this can largely be explained by its importance in those regions that were most strongly affected by the economic crisis. Related production variety, on the other hand, has a significant positive effect on employment growth only in the non-crisis regions, hinting at the growth-enhancing role of relatedness in regional diversification during more normal economic times. Both relatedness and diversity therefore matter for economic performance - albeit for different types of regions and over different time horizons - and striking the right balance between them will be crucial for the success of Smart Specialisation Strategies. In particular, the results highlight the potential benefits of diversifying beyond closely related economic and innovation activities, indicating that unrelated diversification should not be entirely disregarded as an option in the design of Smart Specialisation Policies, even though the associated risk of failure is considerably higher.

The report finally takes a closer look at a few regions that the analysis identified as showing particularly interesting patterns (the case studies are presented in the appendix). The focus of these case studies is to present the statistical material for selected EU regions in detail and discuss it on the background of additional material available from existing studies such as the Regional Innovation Scoreboard, the Regional Innovation Monitor, as well as from other pertinent case studies and material. The qualitative information overall confirms the quantitative results although not all relevant aspects could have been covered.

Overall, the results of this report and its policy implications underscore that ***Smart Specialisation policies require a smooth coordination of a larger set of diverse policy measures that take into account both the local context and all the involved players*** rather than a perfect setup of single policies.

# CONTENT

# Chapter 1.
# INTRODUCTION

The aim of this study is to investigate the development of new industrial specialisations and the process of export diversification both at the country and the regional level for the EU Member States over time. It will examine to what extent these processes show path dependent properties and whether capabilities to generate and absorb new knowledge can contribute to shift persistent development trajectories. Finally, the study will also provide insights on the diversification potentials across countries and regions in the EU.

The development of unique specialisations and the exploitation of diversification potentials stand at the core of recent efforts by the European Union to promote economic development and growth of European regions. Smart Specialisation Strategies (3S) have become the primary policy-prioritization logic in this context and inform nowadays important domains of EU policy making such as EU Cohesion Policy (European Commission 2011c) as well as a number of initiatives related to the New Industrial Policy agenda put forward by the EC recently (European Commission 2012a). This policy concept has been developed to address the productivity gap between the USA and European countries that has emerged in the 1990s and has shown a high degree of persistency ever since. While in the past the EU has pursued horizontal policy approaches to address this problem it has recently realigned its policies towards 3S. The reason for this change in strategy is due to an increasingly stronger evidence attributing the productivity gap primarily to differences in industrial specialisation, the relatively less efficient translation of R&D investments into higher productivity within given industries, and differentials in ICT adoption and diffusion in ICT-using industries (cf. McCann and Ortega-Argiles 2013). Regions have been identified as the appropriate domain for addressing these issues, as many studies have shown that in a large number of European regions there is a weak relationship between R&D investment, regional training specialisations and the structure of local and regional economic activities (cf. Boschma, Minondo and Navarro 2012).

Smart Specialisation Strategies address the capacity of a country or region to develop new specialties and generate structural change via research and innovation. The aim is however not only to foster the creation of new enterprises and the development of new and improved products and processes. It is also to promote economic and technological diversification by drawing on the existing knowledge base and developing it further by deepening and broadening it. Smart Specialisation Strategies thus imply putting in place a process whereby diversification in new (and related) specialities can be facilitated thanks to targeted government intervention in order to support the most promising new activities in terms of discovery, spillovers and structural change.

In a recent paper Foray, David and Hall (2011) have characterised the smart specialisation policy process as consisting of three subsequent phases that should be promoted by public policy. Following Hausmann and Rodrik (2003) the first phase consists of a process of entrepreneurial discovery revealing what a country or a region do best in terms of R&D and innovation and how existing capabilities can be linked up to new knowledge that would permit the diversification of existing productive structures. The second phase is one of imitative entry and agglomeration. Successful entrepreneurial discovery paired with imperfect appropriation will encourage entry by competitors such that regional industrial agglomerations emerge. In its final phase, the smart specialisation process will then lead to a structural evolution in which these regional agglomerations start to change.

The changes induced by 3S can take one of four distinct patterns: The first pattern involves the transition of existing activities to new ones by extending the range of application of given engineering and manufacturing capabilities to another, technologically related domain. This is the case, if for instance, textile firms that have hitherto produced textiles for apparel move into high-tech textile production for industrial applications. The second pattern involves the modernisation of existing capabilities by combining them, for instance, with general-purpose technologies (GPTs) such as information technology or nanotechnology thereby boosting productivity and extending the potential range of applications. The third pattern involves classical diversification processes exploiting economies of scope such as the development of new lines of productive activities. Finally, the fourth pattern implies the radical formation of entirely new domains of enterprises in a region or country by combining local expertise with R&D or management experience from outside.

The development of unique specialisations is a longstanding topic in the analysis of trade and international competitiveness of countries. Indeed, economic trade and development theories have consistently argued that economic activities are not spread homogeneously in space, but that they cluster geographically. The classical Ricardian theory of trade, for instance, shows that a country (or a region) will specialise in the production of goods where it has a relative technological or resource based advantage and import those goods where it has a relative disadvantage. This will hold even in the case where a country has an absolute advantage in the production of all goods over its competitors. Hence, national or regional specialisations emerge as a consequence of comparative advantage. In the neoclassical extension of this theory Heckscher and Ohlin state that in the long run such geographical specialisations will only persist due to differences in resource endowments. This theory rests on the assumptions of perfect technology diffusion and wage equalisation among trading partners which eliminates long-run differences in technology and productivity.

However, such convergence and a purely resource based specialisation are unlikely to take place in the presence of geographically concentrated increasing returns due to scale economies as well as external or agglomeration effects. A number of contributions to aggregate growth theory (see for instance Atkinson and Stiglitz 1969; David 1975; Broadberry 1994) and Schumpeterian trade theory (e.g. Dosi, Soete and Pavitt 1990b) have argued that increasing returns induced by geographically clustered external economies such as knowledge spillovers may give rise to persistent disparities in technological and economic development across countries and regions. They may generate considerable switching costs. In the event of changes in relative factor prices of inputs companies hence might not replace an existing inefficient technology with one out of a set of existing alternatives, if more efficient technologies are characterised by different factor proportions. Rather they will try to overcome resulting constraints through innovation in the technological neighbourhood of the technological alternatives already in use (cf. Antonelli 1998, 2006).

These insights have been taken up and developed further by recent developments in economic geography. A number of studies have presented both theoretical and empirical evidence that "localised capabilities" that are associated with a particular knowledge and competence base as well as a related specific institutional environment accumulate at the regional level (cf. Storper 1995; cf. Maskell and Malmberg 1999). They have also shown that localised capabilities operate as a source of regional diversification. Regions are more likely to expand and diversify into industries that are closely related to their existing activities. Frenken and Boschma (2011) refer to this as "regional branching". Such branching processes can be also observed in the development of new export specialisations (Hidalgo et al. 2007; Reinstaller 2015), in the exit and entry of plants (Klepper 2006, 2010; Neffke et al. 2013), or the development of new knowledge specialisations (Kogler, Rigby and Tucker 2013; Rigby 2013; Colombelli, Quatraro and Krafft 2014).

The diversification process underlying regional branching is best characterised as a development of related varieties in products or knowledge. In this process existing competences are recombined with new economic, technological, organisational or institutional activities. The relatedness in technological and knowledge space between different agents facilitates the absorption of knowledge spillovers as well as factor mobility and substitution across economic activities. Indeed, regions benefit from related variety that fosters firm performance (Boschma and Wenting 2007), regional growth in employment and productivity (Boschma, Minondo and Navarro 2012; Frenken, van Oort and Verburg 2007) or patenting activities (Castaldi, Frenken and Los 2015). Hence, industrial specialisation is an outcome of successful economic development and new specialisations emerge out of existing, related specialisations.

This observed path dependent development has important implications. On the one hand, it may be the source of unique specialisations and thus ensure a high level of international competitiveness of well specialised countries as has been worked out in the previous paragraphs. On the other hand, it may also give rise to development traps (Jankowska, Nagengast and Perea 2012; Metha and Felipe 2014) and regional lock in (Martin and Sunley 2006). These are two sides of the same coin. On which side it falls will depend on the diversification potential that given localised capabilities have, but also on the capability of firms to get access to knowledge that enables related diversification processes. An important question therefore is how regions that are locked-in in specialisations that allow for little diversification potential can leapfrog to more promising development paths.

The literature provides some indications on how to address this problem, as there is evidence that diversification by recombination with unrelated capabilities may enhance technological breakthroughs, whereas diversification through related varieties may support more incremental change (cf. Castaldi, Frenken and Los 2015). Hence, cognitive skills and technologies that allow bridging the cognitive, technological and geographical gap between products, knowledge and other capabilities that are at the core of a regional specialisation and non-core products and capabilities that have the potential to drive diversification processes may play an important role to overcome regional development traps (Menzel 2008).

In the light of this evidence, the following chapters will address the following questions:

- How do processes of export diversification and the emergence of revealed comparative advantages relate to capabilities to generate and apply knowledge at the country level? How are they related to changes in industrial specialisation?
- What are the export diversification potentials of countries and regions, in which sectors and technological fields are they located? Which areas of strengths are under competitive pressure?
- How does the development of new industrial specialisation patterns relate to regional capabilities to generate and absorb knowledge as well as to existing capabilities?
- Can countries or regions with low development potential leapfrog into more sophisticated areas of the product space, and if so, how?
- What is the impact of related (and unrelated) diversification in product and knowledge space on economic performance at the regional level?

In the analyses chapter 2 firstly examines the role of local capabilities for path dependency in industry structures and identifies areas of strength and diversification potentials across EU Member States. The chapter also introduces the main indicators necessary for measuring specialisation and diversification as well as local capabilities in the analyses. Chapter 3 analyses the relationship between national capabilities to generate and apply knowledge and the development of comparative advantages and changes in industrial specialisation at the national level. This chapter provides an econometric analysis of the relationship between specialisation and competitiveness (measured in terms of world market shares) on the one hand and capabilities to generate and absorb knowledge at the other hand. In particular, the chapter focuses on education and skills, innovation activities (measured in terms of patent applications) and knowledge inflows from FDI and capital goods imports.

Chapter 4 breaks down the product space indicators obtained at the national level to the regional level and examines the relationship between knowledge capabilities and (imputed) regional product sophistication and industrial specialisation econometrically at the regional level. The first section of the chapter describes how this break down of the indicators to the regional NUTS 2 level has been carried out. These indicators are analysed jointly with regional indicators on knowledge capabilities. Chapter 5 complements the analysis above by examining the effect of specialisation and diversification patterns on regional economic performance taking into account the heterogeneity of regions.

**Table 1.1 Data sources and use in chapters**

| | Sources | Chapters |
|---|---|---|
| Industrial Specialisation of Countries and Regions | | |
| Country Level | CEPII (BACI) | 2,3,4 |
| Regional Level | BvD (Amadeus), Eurostat (SBS) | 4,5 |
| Education and Skills, Knowledge Absorption and Knowledge Generation | | |
| Skills and Education | Hanushek & Wössmann, Barro & Lee, Eurostat (HRST) | 2,4 |
| Regional Economic Performance | Cambridge Econometrics | 5 |
| Knowledge Generation | OECD (Regpat) | 2,4 |
| Knowledge Inflows | BvD (Amadeus), CEPII (BACI) | 2,4 |
| Product Space and Product Sophistication | | |
| Product Sophistication | CEPII (BACI) | 2,3,4,5 |
| Relatedness | CEPII (BACI) | 3,5 |
| Neighbourhood Density | CEPII (BACI) | 2,3,4 |

Overall, the report takes on different perspectives on the same topic. This requires different data sets and indicators. Table 1.1 summarises the set of data sources the report relies on and indicates which data sources are used in which chapters. The data sources cover all the different aspects relevant for the analyses. Although data and indicators vary across chapters and analyses, the observed patterns are well in line and confirm each other if taking into account their limitations. This is plausible as the indicators used in the analyses are highly disaggregated. The unit of observation[1] are 6-digit product classes (following the HS2002 classification) for analyses at the country level and 4-digit industries (NACE Rev. 2) at the regional level. Hence, the main advantage of this study is based on linking highly disaggregated information to the national and regional institutional context. A detailed overview on the used indicators can be found in the annex (see Table A.20).

[1] The analysis of regional economic performance focuses on aggregate regional employment growth. The unit of analysis in chapter 5 are therefore NUTS2 regions.

## 1.1. CLASSIFYING COUNTRIES BY DIFFERENCES IN TECHNOLOGICAL AND ECONOMIC DEVELOPMENT

The main focus of this study is to understand trade and industrial specialisation patterns of EU Member States. Although the EU-28 countries are in general highly developed when compared to other countries, they also strongly differ concerning their technological stage of development which is of high relevance for this study since these differences strongly impact technological and market opportunities. Countries that are far from the technological frontier typically face lower factor costs and are able to exploit cost advantages, while for countries close to the frontier factor costs are typically high and comparative advantage is based on the capability to innovate. Similarly Lazonick, (2002) claims that the way entrepreneurial activity contributes to the process of economic development cannot be analysed without an understanding of the link between the state of a country's economic development and its innovation activity. Classifying countries according to general technological potential therefore allows sharpening the analysis of the effects of product sophistication and relatedness as well as knowledge capabilities on specialisation patterns of EU countries. In particular, the heterogeneity of countries' economic and social characteristics makes the analysis of a large economic area, such as the EU, difficult and renders statistical inference and comparative insight across the units of observation all but straightforward. All of this, in turn, makes it difficult to draw meaningful policy conclusions. In addition, the smaller the unit of analysis, the greater will be the diversity. Effects are averaged across country data. As most of the relevant product characteristics (such as product sophistication) are determined at the firm level (since innovation occurs essentially at this level), the analysis has to deal with the multiple sources of heterogeneity. One solution is to use country classifications that allow building meaningful groups with respect to technological and economic development in order to analyse specialisation patterns within these sub-groups more accurately.

It is possible to statistically construct a country classification based on the distinction between technology users and technology producers. A technology using country predominantly relies on technology transfer, while a technology producer invests heavily in own R&D. By summing domestic direct and indirect R&D[2] components a measure for the overall technological intensity of a country's production can be obtained. On the other hand, summing up the components of foreign indirect R&D delivers a measure of a country's dependence on foreign technology. Using these two measures and GDP per capita at purchasing power parities (PPP) allows clustering countries within the spectrum from high direct and indirect R&D intensity and high levels of economic development on the one hand to below average direct and indirect R&D intensity and lower income levels. Following Reinstaller and Unterlass (2011), the country groups presented Table 1.2 will be used to sharpen the analyses in this study[3].

**Table 1.2 Country groups by technological and economic development, EU-28**

| Country group | Countries |
|---|---|
| Higher income countries with high direct and indirect R&D intensity: | FI, SE |
| Higher income countries with average direct and indirect R&D intensity: | AT, BE, DE, DK, FR, LU*, NL, UK |
| Average income countries with high indirect and below-average direct R&D: | CZ, EE, HU, IE, SI, SK |
| Higher income countries with below-average direct and indirect R&D intensity: | EL, ES, IT, PT |
| Lower income countries with below-average direct and indirect R&D intensity: | BG, CY*, HR*, LT, LV, MT*, PL, RO |

*Source: based on Reinstaller and Unterlass (2011) * not classified by Reinstaller and Unterlass (2011)*

[2] Direct R&D refers to domestic R&D activities carried out in the country itself. The outcome of these R&D activities is therefore directly integrated in the country's products. Indirect R&D refers to imported R&D embodied in imports (e.g. capital goods). The R&D activities are carried out abroad but are indirectly fed into the domestic production system.

[3] The country groups used here are very similar to those presented in COM(2011) 642 final (European Commission 2011b) characterising industrial structures of EU Member States. The first country group defined there fits the pooled first two country groups used in this report.

# Chapter 2.

# NATIONAL CAPABILITIES AND THE DEVELOPMENT OF COMPARATIVE ADVANTAGE AND INDUSTRIAL SPECIALISATION

## 2.1. INTRODUCTION

The key ingredients of Smart Specialisation Strategies (3S) are on the one hand the identification of areas of strengths and on the other hand the identification of potential avenues to diversify them into new, related domains with high market potential and to support structural adjustments towards these areas. In order to properly understand this approach and make it amenable to empirical analysis some definitions are needed and a number of questions have to be answered. Firstly, the notion of "areas of strength" has to be defined. Secondly, it is necessary to understand which factors influence these areas of strength. Thirdly, it is important to understand also the determinants of diversification processes. Policy conclusions can only be drawn if these aspects have been defined and analysed. This report relies on the following notions:

Product classes or sectors where European producers are able to obtain significant market shares in international trade or have developed a comparative advantage are defined as areas of strength. These indicators capture the international competitiveness of European industries and show considerable persistency over time across countries. Local capabilities and knowledge spillovers between related products are identified and analysed as key factors driving not only international competitiveness at the level of single product classes but also diversification processes. The chapter presents indicators that are valid proxies for local capabilities and potential knowledge spillovers across products in a country that will be in the analytical focus in the different chapters of this report. All indicators and the underlying concepts are presented and discussed in detail in the next section.

The chapter examines the relationship between international competitiveness, local capabilities and untraded technological interdependencies econometrically using the CEPII trade data base for the period 2003-2013. The econometric analysis explicitly takes into account that competitiveness is the outcome of a process of competition in which market and demand conditions play an important role. It controls for these aspects explicitly. The results indicate the strong interdependence and importance of technological interdependencies at the country level in explaining competitiveness and its persistence over time. The model is very robust and will therefore be the analytical template for the later chapters of this report.

In line with the need of 3S policies both to identify areas of strength and diversification potentials across EU Member States, the final part of the chapter will examine and present related evidence. The analysis will aggregate national results from HS 6-digits level into specific NACE 2-digits sectors and key enabling technology (KET) fields. Given the protracted effects of the economic crisis and the emergence of new, significant competitors in international trade, when discussing areas of strengths the chapter will also identify to what extent these areas of strengths have come under economic pressure. Predictions from the econometric model set out in this chapter will be used to identify areas where new comparative advantages could emerge across countries, sectors and technology fields taking into account the most important determinants of international competitiveness. Country fiches detailing these results for each EU member state are included as an extended appendix to this report.

The results of this chapter and the entire report focus on the manufacturing sector. This is largely predetermined by the type of data used and not by an implicit prioritisation of manufacturing over other economic sectors in this study. Indeed, services, such as tourism, or complementarities between business services and manufacturing can be and often are an important source of competitiveness and economic prosperity especially at regional levels. However, the data and methods used in this report do not allow analysing these aspects directly. Nevertheless, this does not significantly limit the validity of the results of this and the following chapters. While these are important limitations of the analysis in this and the following chapters, it is also important to highlight, as the European Commission has underscored in recent communications on industrial policy (European Commission 2012a) that manufacturing is an important source of wealth, income and prosperity in Europe and as such it should be given particular attention.

## 2.2. CONCEPTUAL BACKGROUND AND PRINCIPAL INDICATORS FOR THE IDENTIFICATION OF AREAS OF STRENGTH AND DIVERSIFICATION POTENTIALS

### 2.2.1. Local capabilities as a source of competitive strength and structural sluggishness: a brief review of the literature

Firms produce commodities or services that are differentiated technically from those produced by other firms relying largely on in-house technology, but with some contributions from other firms, and from public knowledge. This makes them different from their competitors and is therefore an important determinant of their competitiveness (cf. Nelson 1991). For this reason, firms have an incentive to improve and diversify their products and services relying upon their existing technological base. Over time they therefore accumulate very specific competencies, which put them even further apart from their competitors. The economic literature refers to this phenomenon as "local (technological) search" and "localised technical change". This is a very pervasive phenomenon which has economic and technical causes (cf. Cantner and Westermann 1998).

The economic explanations for local search focus on the importance of sunk costs and irreversibility in the choice of production techniques. Antonelli (1998), for instance, argues that "all existing capital stocks, both tangible, such as fixed assets, and intangible, such as reputation, experience and competence, have high levels of durability ... Hence it is costly to change both the amount of capital stock as well as the proportions in which it is used with other complementary inputs due to changing market conditions". Specific combinations of tangible and intangible assets linked to one another through complementarities therefore become quasi-fixed factors of production. This has important implication for the analysis of international competitiveness and trade patterns. Persistent patterns of trade cannot be explained in the basis of differences in resource endowments alone anymore. In the presence of irreversibility and switching costs perfect technology diffusion and wage equalisation among trading partners in the long run, as assumed in the traditional Heckscher-Ohlin framework of trade, is no longer feasible. As a consequence, differences in technology and productivity across countries do not easily vanish. Rather, adjustments in technology induced by changes in relative prices will take place along trajectories that are closely related to a spectrum of techniques firms in a country already use. This in turn results in highly persistent patterns of technological and industrial specialisations across countries that are determined by both technology and resource endowments.

The technical explanations for local (technological) search gravitate around the nature of learning processes at the company level and untraded interdependencies. Technical knowledge is localised in the production techniques currently used by a firm, in the markets in which it operates, in existing information channels among firms, customers, suppliers and external sources of knowledge generation such as research institutes or universities. This knowledge accumulates over time through learning (e.g. learning by doing) and is embodied in individuals, company routines or technological blueprints (e.g. Nelson and Winter 1982; Dosi 1988).[4] These routines are perpetuated and developed further to improve the established products. This product specific localised knowledge accumulation is important to achieve high levels of productivity. It enables firms to exploit existing economic opportunities related to their own idiosyncratic technological or organisational capabilities. In order to explore new opportunities, however, companies need to constantly tap into external knowledge sources. Hence, firms have to strike a balance between on the one hand deepening their knowledge related to specific product or services, and on the other hand broadening their knowledge base in order to be able to diversify into new products.

Cohen and Levinthal (1989, 1990) have argued that firms can understand, absorb and implement external knowledge when it is close to their own knowledge base. In other words, effective knowledge transfer between firms and external sources of knowledge (such as other firms, research institutes etc.) requires absorptive capacity and cognitive proximity to enable effective communication and hence to ensure that knowledge can spill over (cf. Nooteboom 2000). This implies however, that diversification is a process in which existing cumulated capabilities are constantly broadened and developed further. In this way firms leverage intertemporal economies of scope (cf. Helfat and Raubitschek 2000; Breschi, Lissoni and Malerba 2003) when they diversify into products that are technologically related to their current products. The process of product development and innovation is thus highly cumulative and dependent on the sequence of past choices, and innovative search outcomes at the firm level are likely to be serially correlated in time. Hence, the evolution of capabilities and the

4 Separate routines are used for each distinct product a firm produces. Each product, in turn requires separate routines for R&D, marketing, management and the other main functions involved in operating business. These routines prescribe procedures that all members in the firm must adhere to when making decisions.

development and installation of new routines that result from the interplay between local learning and the development of absorptive capacities governs both the competitiveness of firms (in the sense of their capabilities to capture market shares or develop entirely new markets), and choices about market entry and exit.

This is not only true for established firms diversifying into new markets, but also for the emergence of new industries driven by new firms. Klepper and Simons (2000), for instance, show for the U.S. television receiver industry, that new industries grown out of old industries. This is the outcome of a process of recombination of competencies from different sectors. The importance of cumulated competences emerges from a study by Klepper (2007). He has shown that spin-offs have a higher survival probability if their founder had prior experience in a related industry. In another paper, Klepper (2001) also shows that this is directly related to the transfer of routines between established firms and their spin-offs. Finally, Klepper and Buenstorf (2010) have shown that firm entry typically clusters also geographically because of the (localised) supply of capable entrants, which in turn is strongly influenced by localised knowledge and production externalities. Hence, local learning, cumulated capabilities and related externalities play an important role not only for growth and competitiveness at the company level, but also for the branching of new industries out of established ones, and thus also in structural evolution of industries in the long-run (Neffke and Henning 2008; Neffke, Henning and Boschma 2011).

The externalities that play an important role for the international competitiveness of firms and industrial restructuring over time can be thought of as untraded interdependencies related to technological complementarities, untraded technological interdependencies and information flows, common infrastructures and economic, technical or educational institutions, various sorts of dynamic economies of scale, and so forth (Dosi, Soete and Pavitt 1990a). These interdependencies are instrumental in generating common experiences and skills embodied in people and organisations, and capabilities overflowing from on economic activity to another. The localised knowledge flows do not necessarily correspond to the flows of commodities, and represent a truly collective asset of groups of firms or industries in a country. They are a fundamental ingredient in the innovation process and determine incentives and constraints to the innovation process. Companies or sectors that are better embedded in these knowledge flows will also be able to benefit more from and translate them into competitive advantages. This will give rise to distinct specialisation patterns, as those companies and sectors that are best able to benefit from these externalities and cumulated capabilities will also be able to learn, innovate, generate new and improved products and hence improve productivity faster, than those companies and sectors that are not equally well embedded in these linkages (cf. Reinstaller 2015). This will in turn have an important impact on the composition of trade. Hence, untraded interdependencies play a crucial role in explaining in patterns of industrial specialisation and trade across countries.

To summarise, the presence of these economic and technological determinants for local learning and accumulation of capabilities has a number of consequences for the analyses of smart specialisation in general and this study in particular:

- Local learning and untraded interdependencies will result in considerable heterogeneity across firm, both in a horizontal sense (in terms of applied techniques), but also in a vertical sense (in terms of efficiency);
- Cumulativeness, asset and knowledge specificity as well as technological relatedness go along with a degree of stability in industry structures and specialisations. A high level of persistency of comparative advantages and specialisations should be observed;
- Under the presence of technical spillovers it is likely to find groups of firms with similar techniques but with different technical efficiency;
- If untraded interdependencies and related spillovers are stronger at the country or the regional level (relative to international knowledge flows) it is likely to observe specific national patterns of specialisation related to spillovers and untraded interdependencies.

While cumulated, localised knowledge and untraded interdependencies are a significant determinant of innovation and a driver of productivity and competitiveness, they are also an important source of path dependence which becomes manifest also in the persistency of comparative advantage and industrial specialisations across countries. Looking at the phenomenon of technological search and the take-up of economic opportunity from a more fundamental perspective, on has the think of technology as an assemblage of practices or routines and other components (cf. Arthur 2009). This implies that interdependencies and feedbacks exist within and across firm boundaries between routines, technologies, companies or even sectors. These interdependencies and related processes of knowledge accumulation are a source of dynamically increasing returns (i.e. returns that increase over time due to positive feedbacks between the knowledge base of related firms and the knowledge spillovers), complex feedback structures and indivisibilities. There is a large body of both theoretical and empirical literature that shows that under such circumstances it is very difficult to break away from established technological and productive systems and their development trajectories (cf. Milgrom and Roberts 1990, 1995; Auerwald et al. 2000; Fleming and Sorenson 2003). Hence, local learning and untraded interdependencies are both a source of competitive advantage and a potential source of path dependent development that constrain technological search and limit the potentials for the exploration of economic opportunities. For diversification processes this implies that for any given specialisation it will be difficult to diversify into technologies or industries that are only weakly related to established specialisations. Diversification opportunities are likely to lie in their neighbourhood. In this rests the danger that if local knowledge bases become obsolete over time or come under competitive pressure due to imitation or substitution processes also structural weaknesses will be more pervasive, i.e. affect a larger number of business and cluster geographically. It will also be more difficult to overcome such structural weaknesses.

To summarise, this brief review of the literature has shown that areas of strengths develop out of processes of localised learning and knowledge accumulation in an economy. These patterns are reinforced through positive feedback loops untraded interdependencies create in a regional or national context. While these processes of knowledge accumulation and knowledge transfer favour the development of specialisations and competitiveness in specific technological fields, they can also be a source of persistence and even path dependence in an economy that make structural adjustments sluggish. Potentially they limit and constrain the development of new specialisations and structural change in the business sector of a country in as they favour diversification mostly in technologically related domains. This will be explored further in this chapter.

### 2.2.2. Measuring areas of strength, product relatedness and sophistication

*Areas of strength in international trade: Comparative advantages and world market shares*

Throughout this study revealed comparative advantages and world market shares European producers are able to obtain in international trade and production will be used as the key measures of competitiveness. Box 2.1 describes both indicators in detail. They should however be considered carefully. As Dosi, Soete and Pavitt (1990a) argue, “competitiveness” is an absolute concept reflecting absolute (technological) advantages in the sense that it is independent of an intranational comparison of the activities in which a country is “better” or “worse” at. It rather compares either a country or a single activity to the rest of the world. At the country level it reflects the capability of a country to produce innovative commodities and to use process innovations more efficiently or quickly than other countries reducing the input coefficients in production. More capable countries will generally participate more intensely in international trade and achieve higher market shares. Similarly, more capable exporters in a country will also be able to achieve higher world market shares for the products they export. Hence, world market shares reflect advantages relative to the rest of the world and international asymmetries in technological capabilities. These largely determine international trade patterns.[5]

World market shares are therefore distinct from comparative advantages in as the latter relate to relative efficiencies in an intersectoral, intranational comparision of capabilities. This is reflected in measures of revealed comparative advantage also used in these analyses. Measures of revealed comparative advantage are the ratio of two absolute measures of competitiveness, namely that of the country (in terms of the world market shares it achieves) and that of a specific activity or sector (in terms of the world market shares the country is able to capture at these levels of disaggregation). As such comparative advantages are driven by the identical factors that determine absolute advantages at the country and at the level of activities of sectors. However, when using these measures it has to be kept in mind, that technological levels (in terms of productivity levels) differ more across countries than intersectorally within countries. As a consequence cross country comparisons of comparative advantages in specific sectors should be interpreted cautiously. If two countries, one with high and the other with low productivity have a comparative advantage in the same sector or product class this implies only that these industries are more efficient than many other industries in that country. It does not imply that the industry in the low productivity country will be able to capture large market shares in international trade; rather it does so only relatively better than the other industries in its home country. Box 2.4 on page 24 provides a more formal discussion of this point. Box 2.1 below shows how these indicators have been calculated.

5 Relative factor costs play a major role influencing trade patterns mostly at equal or comparable levels of technology (in terms of productivity): in this case countries with higher real wages will lose market shares relative to those with lower wages. Hence, if capabilities are easy to acquire and imitate more productive countries will specialise in products requiring higher levels of technological capabilities (cf. Hausmann, Hwang and Rodrik 2007). Comparative advantage and disadvantage at the country level will instead be determined by the relationship between sectoral/activity specific wage rates and the average levels of technology of the country. Comparative advantages will develop in those sectors that have the highest level of technological capabilities in the country, respectively in those sectors where the gap in capabilities relative to the world leaders is smallest.

**Box 2.1 Revealed Comparative Advantage (RCA) and World Market Shares (WMS)**

If variable $x_{c,p}$ represents the value of exports of country $c$ in product $p$, and $X_c$ is the total value of exports of country c, World Market Shares (WMS) are defined as:

(F1) $WMS_{c,p} = \frac{x_{c,p}}{\sum_c x_{c,p}}$, with WMS $\in [0;1]$

World market shares are a measure for the competitiveness of a country in terms of its capability to gain significant world market shares in the products it exports.

Using the same definition of a country's exports as above, the Revealed Comparative Advantage (RCA) is defined as:

(F2) $RCA_{c,p} = \frac{x_{c,p}}{X_c} / \sum_c \frac{x_{c,p}}{X_c}$, with RCA $\in [0;\infty[$

RCAs can provide a demarcation regarding whether or not a given country enjoys a comparative advantage in a given product (dichotomous measure), i.e. RCA ≥ 1 indicates the country has a comparative advantage in the given product). On the other hand, RCA values can quantify the degree of comparative advantage of a country in a given product. RCA values increase the higher the country's world market shares in the give product are compared to the country's overall world market share. The marginal increase of the RCA is even higher, if total world trade volumes are low.

For the empirical analysis (in particular in chapters 2 and 4) an alternative version of RCA values is also used. The RCA defined in (F2) is transformed into:

(F3) $SRCA_{c,p} = \frac{\frac{RCA-1}{RCA+1}+1}{2}$, with $S$RCA $\in [0;1[$

The threshold for having a comparative advantage is 0.5 for the SRCA (equals unity for the RCA).

### *Product relatedness using the product space approach*

It has been argued earlier that untraded interdependencies between sectors, technologies and firms are of primary importance in the process of technical change and hence in the organisation of production and innovation in a country. Experiences and skills embodied in people and organisations, capabilities overflowing from one economic activity to another, which organise the context that determines different incentives/stimuli/constraints to the innovation process for any given set of strictly economic signals (i.e. relative prices, income distribution etc.). They are an important determinant of international competitiveness. Given the highly intangible and complex nature of these interdependencies it is a challenge for the empirical analysis of international competitiveness to develop indicators that are able to adequately proxy them.

Recent developments in the analysis of trade patterns that have led to the establishment of the so-called product space approach (Hidalgo et al. 2007) make it possible to empirically assess the importance of these untraded interdependencies. Hausmann and Klinger (2007) have developed indicators to analyse the product space. They are all based on the idea of proximity between traded commodities. This *proximity* is defined in terms of the conditional probability of countries having a comparative advantage in any two pairs of commodities at the same time. This is a measure of relatedness that is based on outcomes in international trade and is a global characteristic of each product class. From this proximity measure it is then possible to develop a country-product level indicator that relates this product level information to the product mix a country produces and successfully exports. This indicator measures how close a country is to products for which it is a significant exporter. It is the sum of proximities from a particular product to all other products that are exported divided by the sum of proximities of all products. Hidalgo et al. (2007) and Hausmann and Klinger (2007) call it "density". The report will refer to this indicator as "*product neighbourhood density*" to distinguish it from the statistical notion of density. Hausmann and Klinger (2007) show that the "product neighbourhood density" captures the factor substitutability between products, i.e. to what extent factors used to produce one good can be used to produce another good. It can therefore be interpreted on the one hand as a measure for joint cumulated capabilities and untraded interdependencies and on the other hand also as a measure for the embeddedness of a product in the productive system of an economy.

Given the earlier discussions about the importance of untraded interdependencies as a determinant of absolute advantage one should expect this indicator to be a good predictor for the likelihood that a country with a specific product mix can develop a comparative advantage in another product. This will be assessed in the econometric analysis presented in this chapter. Box 2.2 provides the technical details for each of the measures introduced here.

**Box 2.2 Network measures for the product space**

Hidalgo et al. (2007) define the product space as a network of related products, and not as in Hidalgo (2009), discussed in section 0, as a bi-partite network linking countries to products. To construct this network, they define a proximity measure, $\varphi_{i,j}$, between two products i and j as the pairwise conditional probability $P$ of a country exporting one good given that it exports another. This measure is defined as follows:

(F4) $$\varphi_{i,j} = min\{P(RCA_i|RCA_j), P(RCA_j|RCA_i)\},\ (\textit{proximity})$$

where $RCA_i$ means that a country has a revealed comparative advantage (RCA) for product i and is therefore a significant exporter of that product. The RCA is taken in order to ensure that marginal exports do not introduce noise into the data. The minimum is taken to avoid that if a country would be a sole exporter of a good the conditional probability would take on the value 1. By taking the minimum of the reciprocal relationship this problem is avoided. Hausmann and Klinger (2007) provide a detailed discussion of this measure. Proximity is therefore a measure that links any product to any other product traded in the world. In terms of a network, the proximity can be conceived as the edges of the network with the products being its nodes.

In order to assess the likelihood that a product becomes a significant export in a country Hidalgo et al. (2007) define a measure called *density*. The report refers to this indicator as *product neighbourhood density* to distinguish it from the statistical notion of density. It measures the average proximity of a product to a countries current productive structure. For products for which the country is not a yet a significant producer this measure therefore indicates how embedded the product would be and by implication to what extent complementary capabilities are already available in a country. It therefore captures the likelihood that a country develops a comparative advantage in any product. The product neighbourhood density $\omega_j^k$ is calculated as follows:

(F5) $$\omega_j^k = \sum_i x_i \ \varphi_{i,j} / \sum_i \varphi_{i,j},\ (\textit{product neighbourhood density})$$

where $x_i$ is unity if product *i* has an RCA>1 in country *k*. The product neighbourhood density takes on the value 1 if a country produces all *i* products to which product *j* is connected in the product space. The product neighbourhood density is therefore normalised between 0 and 1 and takes on the maximum when a product is connected to all other products in the product mix of a country.

### *Product sophistication*

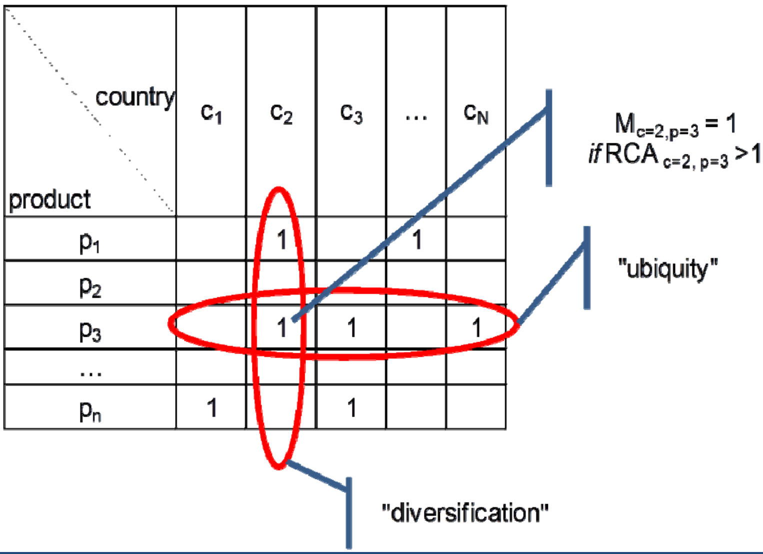
Smart Specialisation Strategies attach high importance to the diversification of industries and structural change. Processes of diversification require combining different types of knowledge to generate new or better products as well as production processes. Already Schumpeter has argued that "to produce means to combine materials and forces within our reach…. To produce other things or the same things by a different method means to combine these materials and forces differently. Changes in the economy therefore arise from "new combinations of productive means." (Schumpeter 1934). New combinations are important drivers of economic growth. Weitzman (1998) and also Arthur (2009), for instance, conceive economic growth as a process where technologies inherit parts from other technologies that preceded them. Novel technologies and products then arise by combination of existing technologies. The stock of existing technologies provides the parts for the combination, so the growth process is highly cumulative. The possibility to generate new products and technologies through recombination presents essentially an unlimited source for growth. Hence, as Weitzman (1998) emphasises, the limits to growth lie not in the ability to generate new ideas, but to transform these into a usable form and exploit them economically. The existing stock of knowledge and the capability of a country to generate products that are more apt for recombination is therefore important to develop and sustain competitiveness (cf. Hanel, Kauffman and Thurner 2007).

For the 3S agenda it is important to understand the key drivers of diversification and knowledge recombination, and what public policies can influence and improve them. However, such an analysis requires indicators that capture to what extent the products a country exports are the result of such diversification and recombination processes. By exploring which countries export certain products and how common certain products are across countries it is possible to this type of information. Hausmann and Hidalgo have proposed an indicator that turns out to be very useful for such an analysis (see Hidalgo and Hausmann 2009; Hausmann and Hidalgo 2011). The key assumption underlying the empirical approach of Hausman and Hidalgo is that countries need a large set of complementary and non-tradable inputs they refer to as capabilities.[6] If countries differ in these capabilities and products differ in the type of capabilities that are needed to produce and successfully trade them, countries with a broader set of capabilities will be more diversified. Trade patterns therefore capture the breadth of the knowledge

6 Hidalgo and Hausmann (2009) see capabilities as property rights, regulation, infrastructure, specific labour skills and so forth.

base of a country. On the other hand, products that require more capabilities will be successfully exported only by those countries that have these capabilities and as a consequence they will be more exclusive (or less ubiquitous). Hence, the more diversified a country is in terms of the products it produces and the more exclusive (or less ubiquitous) these products are in terms of the number of countries producing and exporting them the more competitive and better performing an economy should be as its product mix represents a unique source of competitive advantage. Trade patterns therefore capture also the depth of the knowledge base (in terms of its specialisation and uniqueness).

**Figure 2.1 Diversification and ubiquity of countries and products**




*Source: Reinstaller et al. 2012*

Hidalgo and Hausmann (2009) construct a network linking products (and by implication their capabilities) to countries. The nodes in this network are therefore all country-product combinations that can be observed in the data. The properties of each node can then be expressed as a combination of the properties of all its neighbours. This approach therefore exploits information from the global trade network to construct indicators that capture important aspects of the level of economic development and the competitiveness of economies. Figure 2.1 gives a first idea on how the country and product indicators proposed by Hidalgo and Hausmann (2009) are constructed.[7] In a first step they calculate the degree of diversification of a country by summing up the number of products in which the country (in the figure e.g. country $c_2$) is a significant exporter by row.[8] The larger this sum the more diversified a country will be. In the same way the characteristics of each product can be calculated by summing up the entries by column to get a measure for the "ubiquity" or exclusivity of a product (in the figure e.g. product $p_3$). The fewer countries export a product the more exclusive (or less ubiquitous) it is. In this way one gets a direct characterisation of each country and each product. However, as countries and products are embedded in a network it is possible also to exploit information on countries exporting similar products to characterise each country using a method which Hidalgo and Hausmann (2009) call the method of reflections (Box 2.3). Hence, in the next step each product will be characterised by the diversification of the countries exporting it with comparative advantage, and each country will be characterised by the average "ubiquity" of the products it exports. In the country product network the direct neighbours of countries are other countries exporting the same product. For products the direct neighbours are other products exported by the same countries. Moving through the network of connections that are two, three or four steps away (cf. Box 2.3) delivers increasingly precise indicators for the capabilities of the economies and products in the sample. The resulting indicators therefore capture the breadth and the depth of the knowledge base of a country (for the country specific indicators) and the revealed depth and breadth of the knowledge base needed to produce a product (for product specific indicators). Table 2.1 provides an interpretation of the indicators that include the information that is up to two steps away from a country or product.

[7] It should be noted that the analysis relies only on exports in which any country is a significant exporter. Hence, countries are linked to a product if the country has a revealed comparative advantage (RCA) in this product. The implicit assumption is therefore that a country commands capabilities or factor endowments that enable this advantage.

[8] Diversification in this context does not imply a comparative advantage in products across many industries or higher product class aggregates but is conceived simply as the number of products in which the country is a significant exporter.

| n | country | product |
|---|---|---|
| | **Table 2.1 Interpretation of the indicators calculated using the Method of Reflections, first three pairs** | |
| 0 | $\boldsymbol{k_{c,0}}$: number of products exported by country *c*, ***diversification*** → *"How many products are exported by country c?"* | $\boldsymbol{k_{p,0}}$: number of countries exporting product *p*, ***ubiquity*** → *"How many countries export product p?"* |
| 1 | $\boldsymbol{k_{c,1}}$: average ubiquity of products exported by country *c* → *"How common are the products exported by country c?"* | $\boldsymbol{k_{p,1}}$: Average diversification of the countries exporting product *p* → *"How diversified are the countries exporting product p?"* |
| 2 | $\boldsymbol{k_{c,2}}$: Average diversification of countries with a similar export basket as country *c* → *"How diversified are countries exporting similar products as those exported by country c?"* | $\boldsymbol{k_{p,2}}$: Average ubiquity of the products exported by countries exporting product p → *"How ubiquitous are the products exported by product p's exporters?"* |

*Source: Abdon et al. 2010, following Hidalgo and Hausmann 2009*

**Box 2.3: The method of reflections to calculate the complexity of productive systems**

If the matrix shown in Figure 2.1 is summed up by row over products p one obtains a measure for the diversification of a country c.

(F6) $k_{c,0} = \sum_p M_{c,p}$ … *diversification*

If on the other hand the matrix is summed up by column one obtains a measure for the ubiquity of comparative advantage in the trade of a specific product p, i.e. a measure that shows how many countries c have a comparative advantage in trading this product.

(F7) $k_{p,0} = \sum_c M_{c,p}$… *ubiquity*

By combining these two indicators it is possible to calculate through recursive substitution how common products are that are exported by a specific country,

(F8) $\rightarrow k_{c,n} = \frac{1}{k_{c,0}} \sum_p M_{c,p}\, k_{p,n-1}$ for $n \geq 1$

and how diversified the countries are that produce a specific product

(F9) $\rightarrow k_{p,n} = \frac{1}{k_{p,0}} \sum_c M_{c,p}\, k_{c,n-1}$ for $n \geq 1$

If formula (F8) goes through an additional iteration the indicator now shows how diversified countries are that export similar products as those exported by country c. An additional iteration for formula (F9) shows then how ubiquitous products are that are exported by product p's exporters. Each additional iteration n adds information on the neighbour of a country or product, that is n steps away from country c or product p. Table 2.1 gives an overview on how the indicators calculated using the Method of Reflection can be interpreted. Higher iterations than those presented in the table are increasingly difficult to interpret. The technical appendix of Hidalgo and Hausmann (2009) provides a simple numerical example.

A difficulty in this method is to establish the upper bound of the count variable n. In other words, how many steps far away from a country or product need to be calculated in order to establish a stable ranking of countries and products? Caldarelli et al. (2012) show that the solution proposed by Hidalgo and Hausmann (2009) who stop the iterations after eighteen or nineteen steps cannot lead to accurate rankings. In the current study the upper bound of n has been established for each year in the sample by means of an algorithm that examines the number of rank changes of products and countries after each iteration. As long as the number of rank changes decreases, iterations are repeated. When stability in ranks is achieved the algorithm stops. The related iteration is indexed with "max". This implies that the values calculated for $k_{c,max}$ and $k_{p,max}$ are not directly comparable over time. To establish comparability the variables have been standardised and the related indicators $\hat{k}_{c,max}$ and $\hat{k}_{p,max}$ therefore represent scores capturing the positioning of a country or product in the distribution of all indicators at a specific moment in time. These scores are then comparable over time.

Throughout this report the terms "product sophistication", "product complexity" or "complexity" will be used interchangeably to refer to the indicator described in Box 2.3. Higher scores of this indicator imply that a product class is typically exported by relatively few countries. More exclusive (or less ubiquitous) products have a strong influence on the competitiveness of countries in the global market. Their exclusivity reflects the presence or absence of very specific capabilities in a country: having exclusive products in the portfolio that are related in terms of the underlying capabilities to other exclusive products is more important than having many products that many other countries produce. On the other hand, higher product complexity scores indicate also that countries exporting such an “exclusive” product are generally also more diversified, i.e. their industries can rely on broader knowledge bases in their productive activities, and as a consequence also the product is likely to draw on a wider variety of capabilities. This has the effect that scarce natural resources that often are exported by very narrowly specialised resource exporting countries will not get high product sophistication scores despite them being exclusive. More importantly however, it captures the likelihood that a product is the result of a recombination of different types of capabilities and knowledge bases. As such the indicator captures the outcome 3S policies aim to achieve, i.e. the diversification of regional or national production systems into activities that on the one hand rely on an established knowledge base, but skilfully recombine it with other knowledge bases to yield unique specialisations and therefore ensure absolute technological advantages and thus high international competitiveness.

## 2.3. DATA AND INDICATORS

### 2.3.1. Data

Trade data are most relevant for calculating the core indicators for this study as described in detail in section 2.2.2. The principal data source is the Base pour l’Analyse du Commerce International (BACI) dataset from the Centre d’Études Prospectives et d’Informations Internationales (CEPII). It contains data for 232 countries and 5,109 product categories classified using the Harmonized System at the 6-digit level (HS6). This study uses data based on HS-codes from the 2002 revision covering the years 2003 till 2013. A detailed description of the data is given by Gaulier and Zignago (2010). The following just highlights some important aspects of this database.

The BACI database builds on the COMTRADE database provided by the United Nations which contains detailed import and export data reported by statistical authorities of close to 200 countries starting from 1962 to the most recent year.[9] A typical record contains the exports of a specific commodity between two countries in a specific year in terms of value (US dollars), weight and supplementary quantity (number of the supplied commodities). The database is continuously updated. COMTRADE provides two sets of series for any given trade flow if both commercial partners report the transaction to the UN. Exports are generally reported on a Free on Board (FOB) basis, while the related imports from the trading partner are reported including Costs for Insurance and Freight (CIF). While the two series should be identical for any given product and year except for the CIF positions, in practice these data prove to be often inconsistent (see Gaulier and Zignago 2010 for a detailed discussion of the causes of these inconsistencies). BACI establishes consistency in the bilateral trade flows reported by the exporting and the importing country. It uses mirror flows to complete missing reportings. It also estimates approximations for the correct CIF costs which are then used to make import and export series between trade partners consistent.

BACI provides also comparable quantities such that unit values that are comparable across countries can be calculated. Values in COMTRADE are reported in thousands of US dollars. Quantities however can be registered in different units of measure (meters, square meters, etc.). Since most of exchanged quantities are reported in tons, Gaulier and Zignago (2010) convert the remaining quantities by estimating implicit rates of conversion of other units into ton units using mirror flows reported in tons by a country and in another unit by the other trading partner. This implies that unit values can be examined for a larger number of commodities.

With regard to the other data sources on trade such as the Eurostat COMEXT database, BACI and the underlying COMTRADE database have the advantage that almost all countries report the country of origin of a product as partner country for imports according to the rules of origin effective in each country. Hence, the term ‘partner country’ in the case of imports does not necessarily imply a direct trading relationship, i.e. if products are shipped or transited via a third country. For the purpose of this study this is an important aspect as the interest relies on developing indicators of local capabilities. Looking at direct trading relationship would distort this picture.

The time window provided by this database ranging from 2003 to 2013 is long enough to capture substantial changes in productive structures and ensure that all major economies are covered consistently. As the most severe changes in political geography (e.g. falling apart of USSR, German unification) have taken place before the starting date of the series ensures that there are no important breaks in the data due to these events. For the

9 http://comtrade.un.org/

calculations presented in the following chapters the data have been filtered in order to reduce the noise in the data. Observations where only a single unit is shipped in a year have been dropped when

- the Country-product-year observations have a quantity greater than 50 and CPI-deflated annual export value (in 1989 dollars) is less than $50,000;
- country-product observations do appear in fewer than two years in the sample.

In addition a number of country-like entities like "Areas not elsewhere specified" are included in COMTRADE and BACI to have consistent accounts for data with insufficient information on the trading partners. These entities have been dropped.

### 2.3.2. Indicators

*Overview*

Table 2.2 shows descriptive statistics for the variables of central importance to this study introduced in the earlier sections of this chapter. The table presents the summary statistics for the EU-28 countries and the world. The first row of the table shows standardised RCA values at the product level. The RCA value is the coefficient resulting from the division of the share a product obtains in the respective country's total exports and the share the product's world exports obtains in total world exports. In order to have a more symmetric distribution of the RCA, the RCA values are transformed following formula (F3) in Box 2.1. Hence, the coefficient equals one half if the two shares correspond to one another. The variation of the coefficient approximates 1 when a country has only a relatively small market share and at the same time a product it exports achieves very large market shares. The indicator instead equals zero if a country does not export a product. World Market Shares (wms) measure the shares of the countries' exports in total world exports of a product. World Market Shares are bounded between zero (if a country does not export a product at all) and 1 (if the country is the only one exporting the given product). World Market Shares are therefore also a measure of competitiveness but do not directly reflect specialisation patterns.

The product neighbourhood density variable (dens) reflects the relatedness of a product to all other products a country produces. By construction the variable is bounded between zero and one. Products with density value close to one are very close to – or at the core of – the production system of a country. Products relatively close to zero are instead more in the periphery of the production system of a country. The indicator can be considered to be a proxy for the potential of any product to absorb external economies specific to a national production system. The mean density across countries is 0.25 which indicates that across countries products are generally not very closely related. The indicator is however also considered to capture potential path-dependencies: The increasing returns related to the absorption of external economies set the production system also on specific development trajectories that are more difficult to leave.

**Table 2.2 Summary statistics – Specialisation and the product space**

| | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| EU-28 | | | | | |
| Standardised RCA (srca) | 1399653 | 0.27 | 0.28 | 0.00 | 1.00 |
| World Market Shares (wms) | 1399653 | 0.01 | 0.04 | 0.00 | 1.00 |
| Neighbourhood Density (dens) | 1399653 | 0.26 | 0.12 | 0.01 | 1.00 |
| Product Sophistication (soph) | 1399653 | 0.00 | 1.00 | -4.57 | 3.37 |
| World | | | | | |
| Standardised RCA (srca) | 3576891 | 0.21 | 0.27 | 0.00 | 1.00 |
| World Market Shares (wms) | 3576891 | 0.01 | 0.05 | 0.00 | 1.00 |
| Neighbourhood Density (dens) | 3576891 | 0.19 | 0.12 | 0.00 | 1.00 |
| Product Sophistication (soph) | 3576891 | 0.00 | 1.00 | -4.57 | 3.37 |

*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

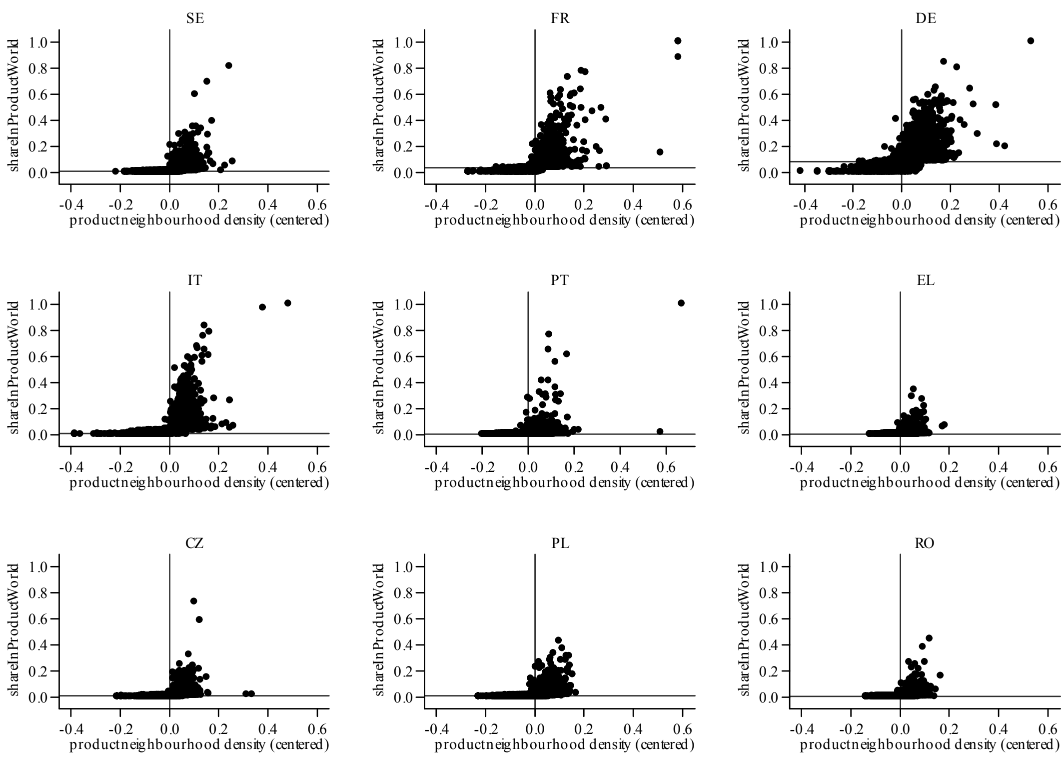
The indicator for product sophistication captures the depth and the breadth of the knowledge base underlying needed to successfully export a product. The indicator is a standardised variable relative to the variation of the underlying complexity values across products at a particular point in time. This standardization is necessary as the network used to calculate the complexity values changes every year and the variables would thus not be comparable over time. Given that the variables have been standardised, the average complexity score across products equals zero. The indicated scores present standard deviations from this mean. As would be expected the standard deviation of the indicator is – due to the standardization – very close to one. Product complexity scores vary between more than -4 and more than +3 standard deviations (see Table 2.2).

*Product relatedness and competitiveness in the EU-28 countries*

In the earlier sections of this report, “product neighbourhood density” has been introduced and discussed as an indicator capturing the untraded interdependencies (e.g. company spin-offs or university-company linkages) and knowledge spillovers (e.g. through labour mobility) in a country. The terms “product neighbourhood density” and “product relatedness” will be used interchangeably in this study. The reason for this is that the indicator can also be interpreted as the embeddedness of a product class in the production system of an economy thus reflecting the capability of its producers to absorb spillovers from other domains of the national economy. As a well embedded product will typically benefit better than other products from these externalities its producers will be able to produce higher quality and/or lower cost products that were previously available. This should be reflected both in the competitiveness of these product classes in international markets and hence in the world market shares its exporters are able to gain.

The following figures present some evidence supporting the conjecture that there is a close correlation between product neighbourhood density and international competitiveness as measured by world market shares a country is able to obtain in a product class, changes in export status, and the development of new specialisations in commodity trade. Figure 2.2 presents figures plotting the product neighbourhood density of a product class against the world market shares it has obtained in the year 2013 for selected EU countries. In these figures the product neighbourhood has been centred insofar as the mean density of the country has been subtracted from the individual values in order to put the different plots on an identical scale. The observed patterns vary across countries but it is evident that with increasing product neighbourhood density the world market shares the countries obtain in each product class increase. For some countries like Portugal or Greece the relationship is flatter, whereas for most other countries beyond a certain neighbourhood density value the market share increases and drops beyond the threshold level necessary to export with comparative advantage. This threshold level is represented by the horizontal line in each plot which equals the world market share of the country in the year 2013. Hence, the figure supports the view that products that are better embedded in the local productive system are also more likely to achieve strong international competitiveness.

**Figure 2.2 Product neighbourhood density and world market share in selected European countries, 2013**

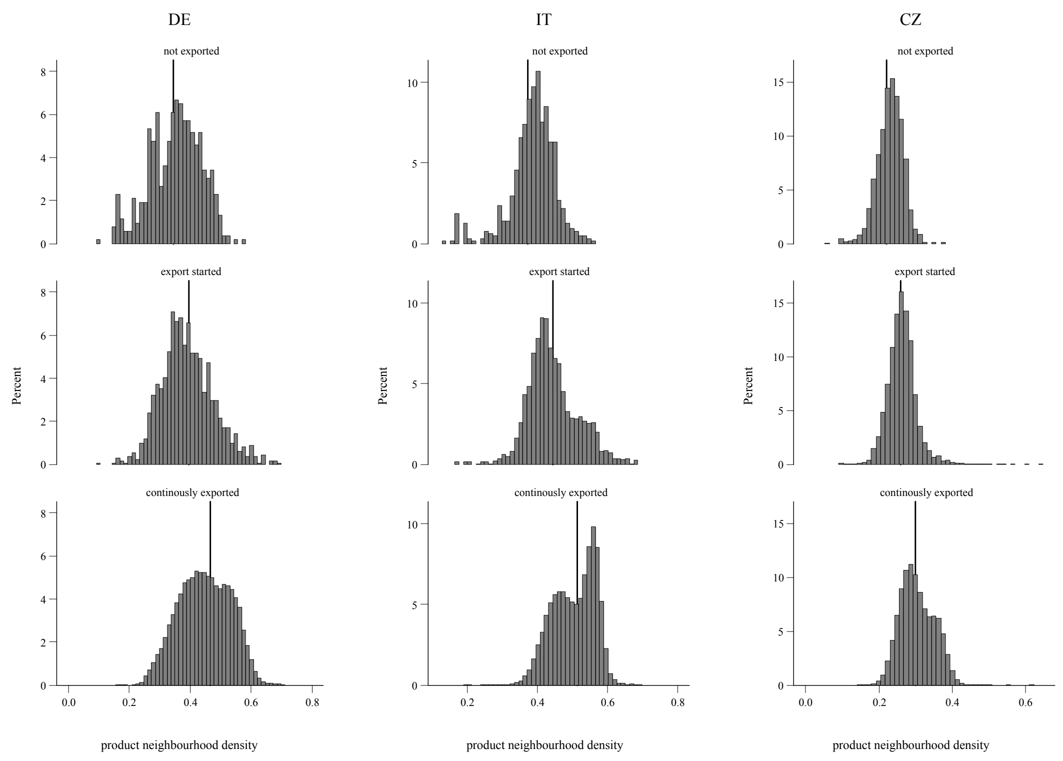



*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

Figure 2.3 present a more dynamic perspective on the relationship between the embeddedness of a product class in the national productive system and changes in export status as well as the development of new comparative advantages. Figure 2.3 shows for a number of selected countries how the distribution of the product neighbourhood density differs across products with different export status. The top panel for each country shows the distribution of the indicator values for products that over the entire period of observation have not been exported by that country. The middle panel instead shows the distribution for those product classes the countries have started to export during the period of observation, and the bottom panel finally shows the distribution for product classes that have been exported throughout the period of observation ranging from 2003 to 2013. The vertical line in each panel shows the average density for each of the shown distributions. It is evident, that the values of the product neighbourhood density are highest for product classes exported over the entire period of observation in each of the countries. The product classes the country has started to export during that period instead take on intermediate values. Finally, the product neighbourhood density is lowest for products that have not been exported. Statistical tests show that the means of the distributions are different from one another in a statistically significant way. The evidence presented in Figure 2.3 therefore suggests that product relatedness supports the development of the extensive margin in trade (entry into new export markets).

The evidence presented so far therefore suggests that product relatedness measured by means of the product neighbourhood density may be used as an indicator for both existing and potential areas of strengths in international trade of a country. Product neighbourhood density may therefore be used as a valid indicator of absolute advantages in trade. This relationship will be examined econometrically in the next section.

**Figure 2.3 Product neighbourhood density and changes in export status for selected countries between 2003 and 2013**

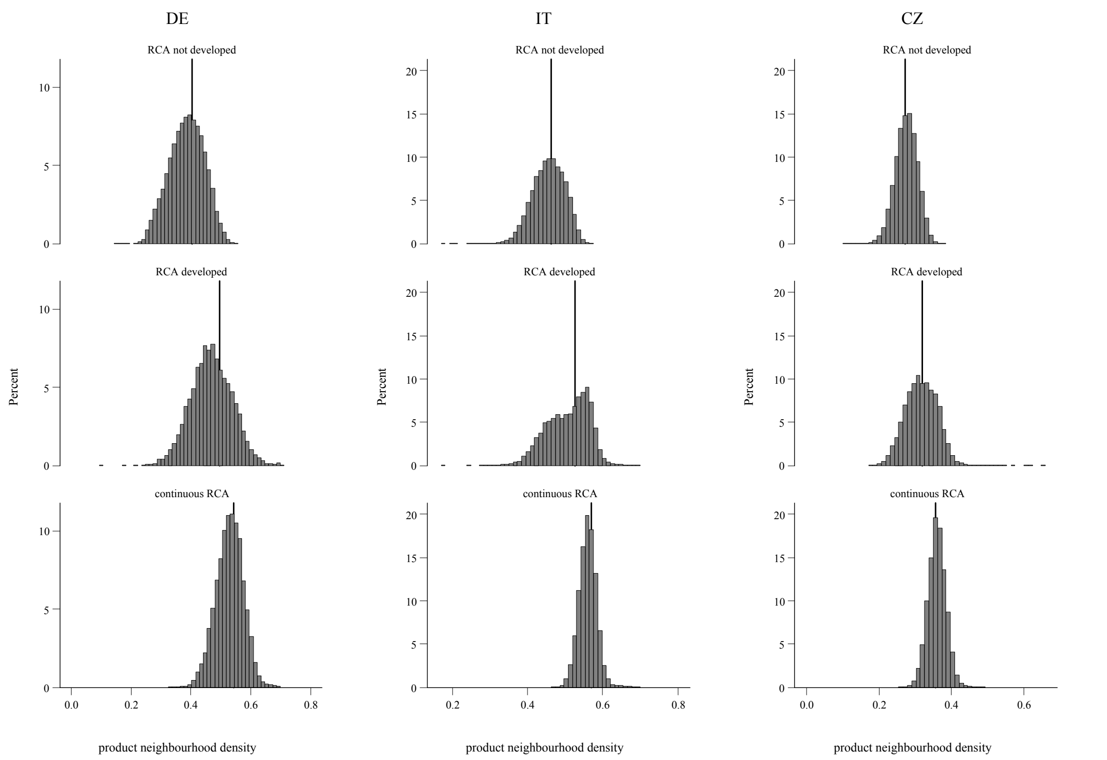



*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

## *Comparative advantage and industrial specialisation*

As the earlier discussion of comparative advantages and the specialisation in trade and industrial reflect relative efficiencies in an intranational intersectoral comparison of capabilities. As such they are determined however by the same factors that determine absolute technological advantages. Hence, the first findings concerning the relationship between of product relatedness and world market shares should also apply to measures of comparative advantage. Figure 2.4 presents identical evidence to Figure 2.3, but this time for the development of comparative advantages. Again, the evidence shows that comparative advantages emerge and persist with increasing embeddedness as measured by the product neighbourhood density. Again statistical tests confirm that the distributions shown in each panel for each country differ in a statically significant way. As the development of new comparative advantages is equivalent to an increase in the intensive margins in trade, the data suggests that product relatedness supports also the increase of intensive margins in trade (the increase of market shares in export markets).

**Figure 2.4 Product Relatedness and the development of comparative advantages for selected countries**



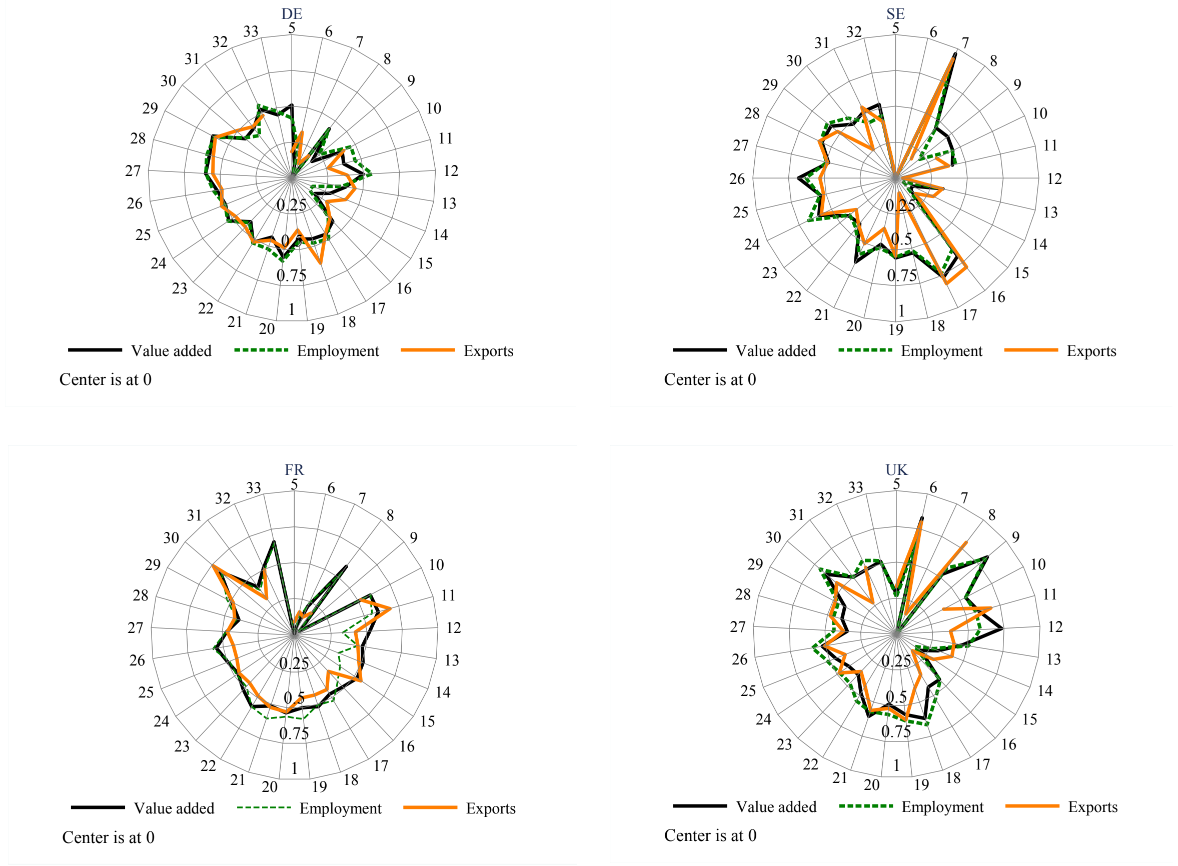

*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

Industrial specialisation patterns can be identified either relying on data related to production activities (i.e. employment or value added) or by the participation on world markets (i.e. revealed comparative advantage). Figure 2.5 gives an indication about the differences when measuring specialisation using different economic indicators. The figure shows revealed comparative advantage (RCA) values calculated on the basis of (1) value added, (2) employment, or (3) exports for the four largest EU Member States (Germany (DE), Spain (ES), France (FR) and United Kingdom (UK)).

All in all, the figures show that while one can observe differences in the RCA values depending on the data used, the alternative calculations show similar patterns. While the magnitude of the RCA values of course differ across indicators used for the calculations, the direction is quite similar (i.e. whether a country has a comparative advantage or not). Interestingly, the differences between employment and value added are not obviously lower than the differences between either value added or employment on the one hand and exports at the other hand. This as a hint that the analysis of specialisation patterns in the study should not be affected that much by the selection of the indicators to calculate RCA values.

This implies also that there are common determinants for these different specialisation patterns and that they can be analysed in a similar fashion. This is of course straightforward: if relative efficiencies drive these specialisation patterns then - ignoring for the moment the sluggishness of adjustment processes - more production factors should be allocated also to more efficient sectors. Hence, patterns of employment and value added share should be highly correlated. On the other hand, more efficient sectors participate also more intensely in trade than less efficient sectors. Therefore, also comparative advantages in trade should be correlated with employment and value added shares. While in reality these interdependencies may be considerably more complex, technical capability and efficiency certainly are common factors influencing different dimensions of specialisation. If untraded interdependencies now are in turn an important determinant of technological efficiency, then the proxy indicator for these interdependencies – product relatedness – should be an important explanatory variable in the development of specialisations.

**Figure 2.5 Standardised revealed comparative advantage – differences between exports, employment and value added for selected EU countries, NACE Rev. 2 2-digit industries**

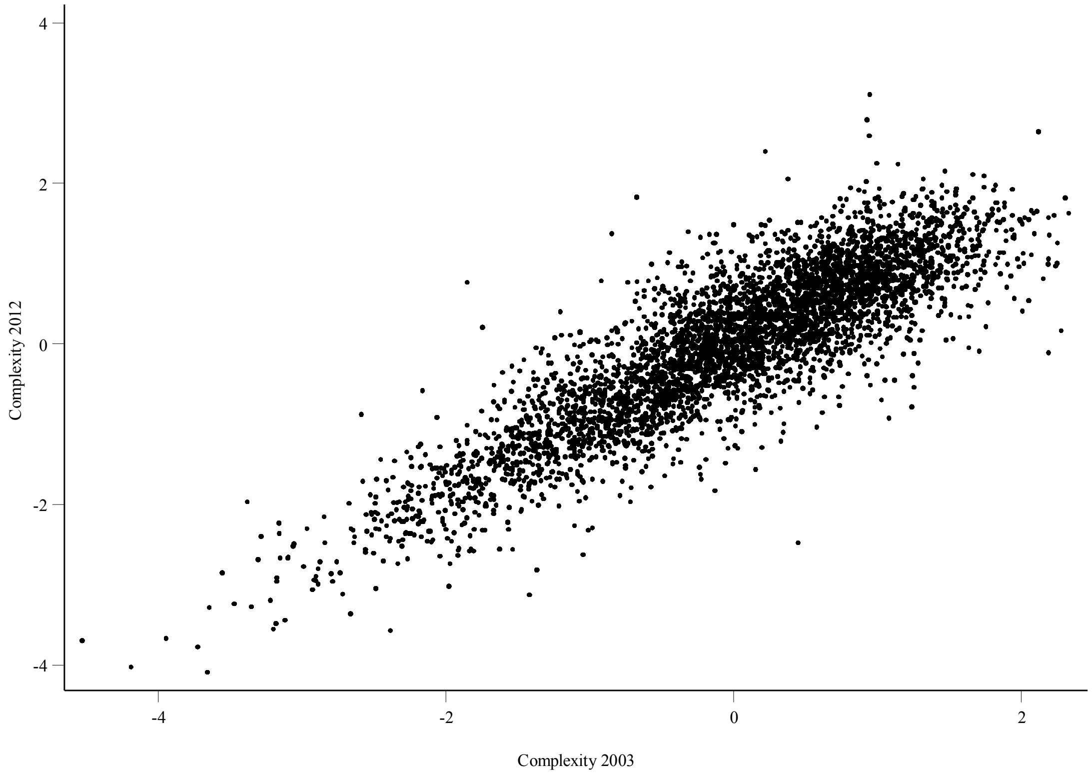



*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010), Eurostat Structural Business Statistics*

### *Revealed sophistication of the product portfolio of EU-28 countries*

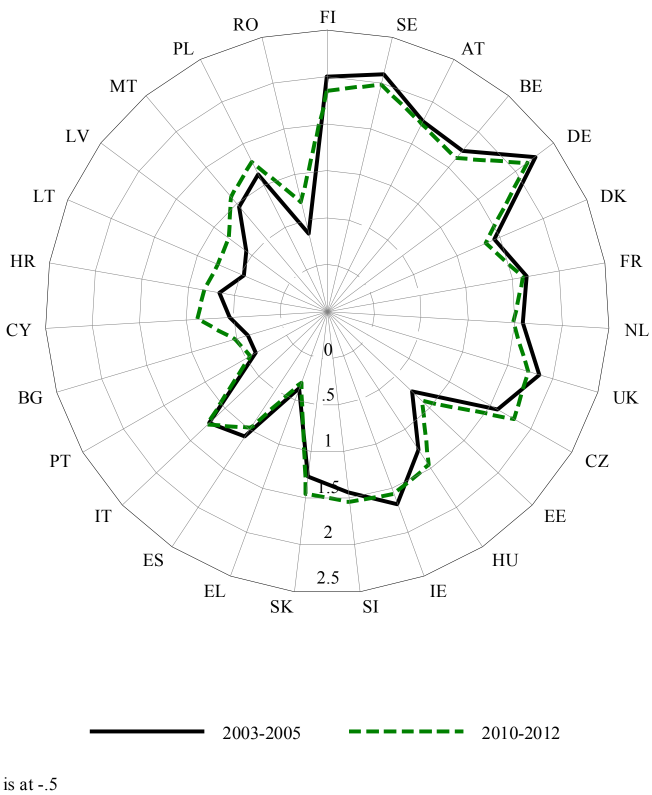
As discussed earlier, the indicator for product sophistication captures the depth and the breadth of the knowledge base underlying needed to successfully export a product. Figure 2.6 plots the complexity scores calculated for each product in 2003 against the complexity scores obtained for the same product in 2012. The figure shows that the complexity scores, while showing some variation over time, are highly persistent and thus strongly correlated over time. The variation over time is caused by countries starting or stopping to produce a product as well as the characteristics of the portfolio of products these countries export with comparative advantage. If countries with more sophisticated products start exporting a commodity with comparative advantage this raises the indicator value, whereas it falls if this portfolio is not very sophisticated.

**Figure 2.6 Persistency of product sophistication over time**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Figure 2.7 Change of the sophistication of a country's product portfolio over time, EU-28 countries by country groups**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

The sophistication of EU-28 countries is on average quite invariant over the observed time frame 2003 to 2012. Figure 2.7 plots the sophistication of the product portfolio of EU member states over the first three years against its counterpart in the last three years. The countries are sorted by the country groups presented in Table 1.2. The graph shows that Germany has the highest average product sophistication of all EU-28 countries but the sophistication slightly decreased over the observed time frame. Sweden (SE) ranked second followed by Finland (FI) which also observed a slight decrease in the sophistication of their product portfolio. On average, the countries that are classified as having high (Finland, FI and Sweden, SE) or at least average direct and indirect R&D intensity (Austria AT, Belgium BE, Germany DE, Denmark DK, France FR, the Netherlands NL and the United Kingdom UK) on average perform better than the other country groups. However, the third country group ("average income countries with high indirect and below average direct R&D") performs also well when looking at the country's product portfolio. The only exception here is Estonia (EE). On the other hand, Eastern European Member States classified as lower income countries with below average direct and indirect R&D intensity also score low in average product sophistication. The lowest product sophistication score is found for Greece (EL) which is also classified having below average direct and indirect R&D intensity but with higher income.

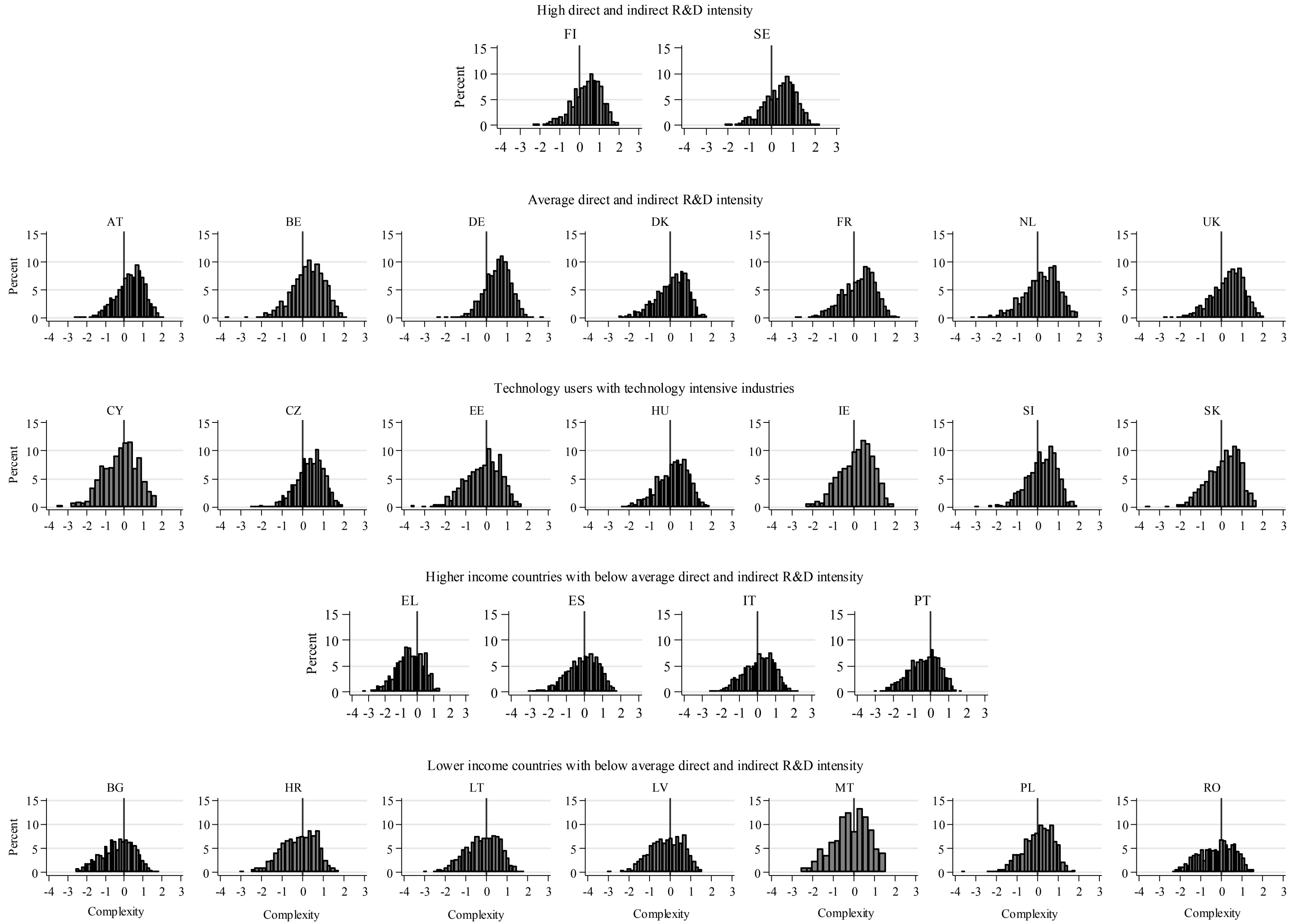
The country grouping also shows a quite robust pattern what concerns changes in time: While the most advanced countries slightly deteriorated in their product portfolio over the observed time frame, those Member States joining the European Union after or in 2004 were able to heavily upgrade it. In particular Romania (RO), but also the Baltic countries Latvia (LV), Lithuania (LT) as well as Cyprus (CY) and Croatia (HR) show significant improvements. On the other hand, previously better performing countries like Finland (FI) and Sweden (SE), but also Belgium (BE), the Netherlands (NL) and the United Kingdom (UK) slightly lost in their level of average product sophistication. Greece (EL) starting at a similar level of product sophistication as Romania (RO) remained unchanged and therefore relatively deteriorated in comparison to the other EU-28 countries over the observed period. Details on the countries' development in average product sophistication over time are summarised in Figure A.4 in the appendix.

Figure 2.8 presents for each of the EU-28 Member States the distribution of product sophistication as measured by the product complexity score for the products these countries exports with comparative advantage for the year 2012. Echoing results in Reinstaller et al. (2012) the figure clearly shows that there is a considerable heterogeneity in the sophistication of the export specialization across the EU. For some countries the portfolio of products exported with comparative advantage is clearly skewed towards complex products whereas for others it is considerably less sophisticated on average. This is also in line with prior results providing evidence on considerable difference in technological content of the manufacturing sectors across EU Member States using sectoral R&D data (cf. Reinstaller and Unterlass 2011).

To conclude this first section, Figure 2.9 plots the product neighbourhood density values of product classes that have consistently been exported with comparative advantage against the relative product sophistication scores. The product neighbourhood density values have again been "centred" insofar, as the country average has been subtracted. Hence, the vertical line in each panel represents the country specific average of the product neighbourhood density. For the product sophistication indicator a score of zero represented by the horizontal reference line indicates an average level of sophistication whereas positive scores stand for above average degrees of product sophistication.

Two aspects are of interest in this figure: first, in line with the evidence presented in this section almost all product classes consistently exported with comparative advantage have product relatedness scores that are well above the country average indicating that these products are indeed highly embedded in localised production structures and capabilities. The second aspect of interest is that for a number of countries such as Germany, France, the United Kingdom or Belgium more sophisticated products seem to be at the core of the exporting manufacturing industries of those countries. For these countries higher product relatedness goes along with higher product complexity. For other Member States such as Portugal, Greece, Rumania or Bulgaria relatively unsophisticated products constitute the competitive core. For other countries again such as Hungary, Poland or Italy the patterns are less distinct.

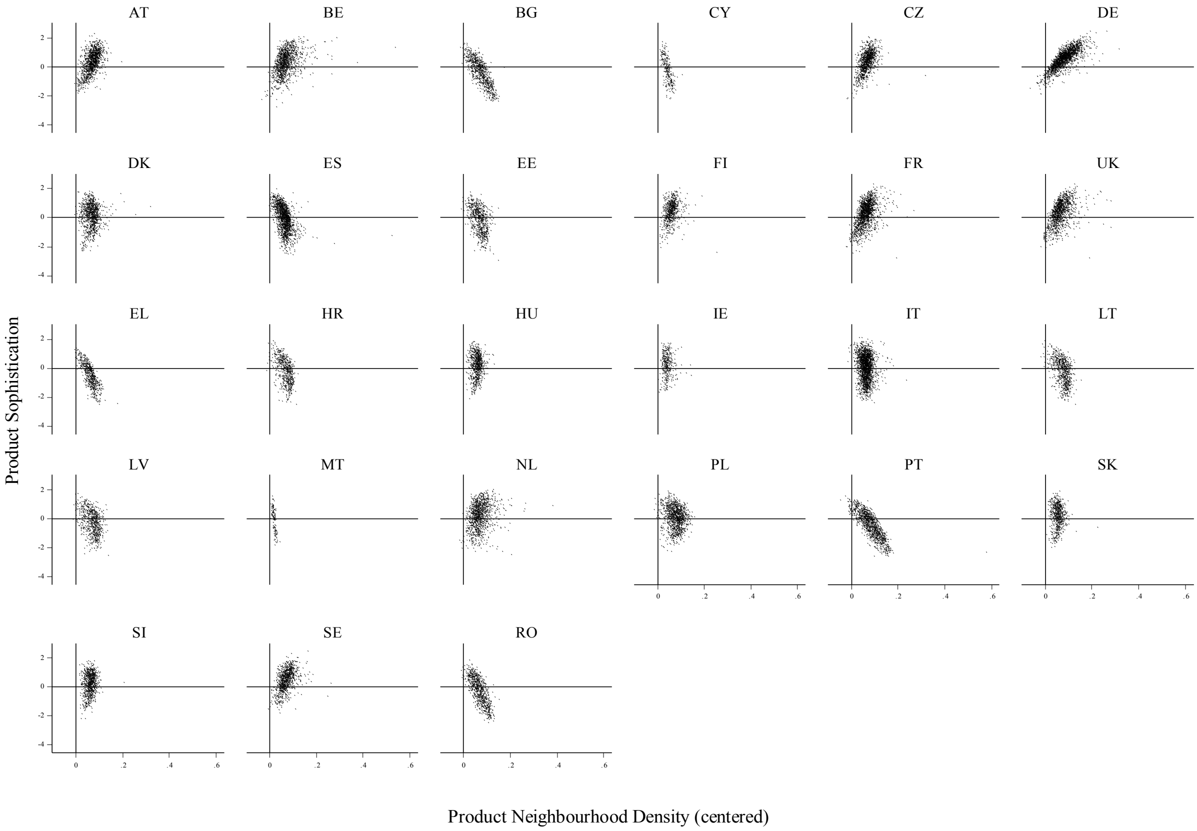
## Figure 2.8 Sophistication of the product portfolio of EU-28 countries




*Note: Histogram of product complexity scores of all products with RCA > 1 by country. Countries are sorted by country groups based on the economic and technological development as presented in Table 1.2*

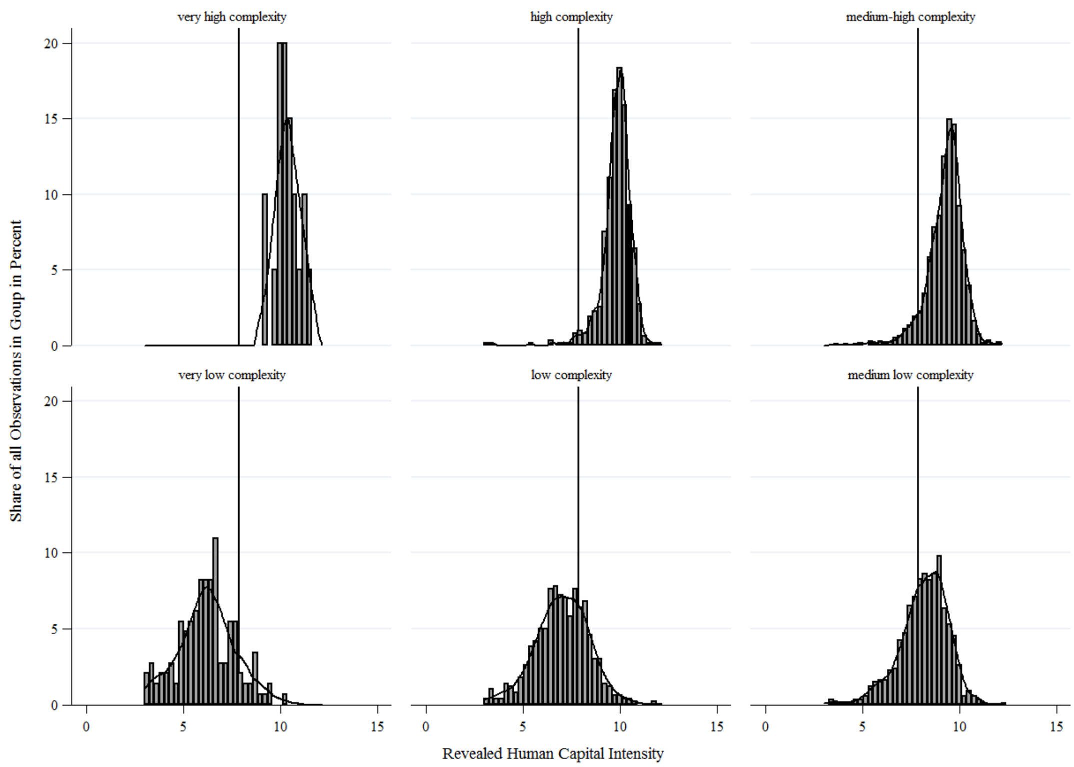
*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Figure 2.9 Centred product neighbourhood density and product sophistication in the areas of strength, EU-28, 2013**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Figure 2.10 Product sophistication and revealed human capital intensities**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

Figure 2.10, finally, shows that higher product sophistication scores go along with higher levels of revealed human capital intensity. This plot classifies products according to the distance their product sophistication scores have from the mean. For instance, products that have a product sophistication score that is more than three standard deviations below the average are classified as having very low complexity, products for which the score is between two and three standard deviations below the mean are classified as having low complexity, and products that are at most one standard deviation below the mean are classified as having a medium-low degree of sophistication. The identical logic applies for products with complexity scores above the mean. The indicator for the revealed human capital intensity has been calculated using the method proposed by Shirotori, Tumurchudur and Cadot (2010) and uses the Barro-Lee data on education attainment across countries over time (Barro and Lee 2013).[10] Higher index values of the educational attainment indicator point at higher average years of attained schooling by the countries exporting a product with comparative advantage. The figure clearly shows that the average educational attainment across countries exporting the product increase for the more complex the products. This evidence supports the interpretation of the indicator as capturing the depth and the breadth of the knowledge base needed to export a specific product. A factor analysis carried out at the country level by Reinstaller et al. (2012) has also shown that the complexity scores reflect a number of indicators on knowledge and human capital creation (such as R&D and tertiary education shares) as well as indicators capturing determinants of diversification of national industries such as foreign direct investment.

[10] http://www.barrolee.com/data/full1.htm

## 2.4. EMPIRICAL ANALYSIS OF THE DETERMINANTS OF COMPETITIVE STRENGTH IN INTERNATIONAL TRADE

### 2.4.1. Competitiveness and local capabilities: Towards an empirical assessment

At the beginning of this chapter it was argued that the competitiveness of a country in exporting specific products is to a large extent determined by the technological capabilities of its exporters. These in turn benefit from untraded interdependencies that have the features of a public good (i.e. an externality in terms of knowledge spillovers) for all producers that share similar capabilities. It was also argued that the effect of these untraded interdependencies would be the stronger the better embedded a product was in a national or regional production system in the sense that its producers are better able to use the local competence base.

This section will test the relationship between international competitiveness captured by world market shares at the product class level and untraded interdependencies proxied through the product relatedness described in detail before econometrically. This is important for this report, as it has been argued before that local capabilities and knowledge spillovers between different local competence bases are not only a source for absolute technological advantage and competitiveness, but also a potential source for path dependence and sluggishness in diversification processes. Both issues are very important for 3S as diversification processes out of existing areas of strengths are a key aspect of this approach.

**Box 2.4 Absolute and relative measures of competitiveness and the importance of technological differences**

Keeping in mind what has been said so far, one can view the international trade performance in a product class or sector of a country in terms of its world market share, $wms_{c,p,t}$, in that aggregate as a function of technological advantage relative to the other exporters active in the international market for $p$ (related amongst other things to untraded interdependencies), $T_{c,p,t}$ , relative costs (e.g. labour costs), $C_{c,p,t}$, and specific forms of industrial organisation such as the market structure or the intensity of intrasectoral competition, $O_{c,p,t}$, as follows (cf. Dosi, Soete and Pavitt 1990a; Reinstaller 2015):

(F10) $$wms_{c,p,t} = f\left(T_{c,p,t}, C_{c,p,t}, O_{c,p,t}\right).$$

This equation represents the determinants of international competitiveness of product $p$ of country $c$ at any time $t$. As performance is defined here relative to the world, $f\left(T_{c,p,t}, C_{c,p,t}, O_{c,p,t}\right)$ captures absolute advantages or disadvantages. Analogously, the international trade performance of country c can be defined:

(F11) $$wms_{c,t} = F\left(T_{c,t}, C_{c,t}, O_{c,t}\right),$$

where $T_{c,t}$, $C_{c,t}$, and $O_{c,t}$ now represent the position of a country $c$ relative to all other countries. As a corollary one sees now that revealed comparative advantage is a ratio of two absolute measures of competitiveness:

(F12) $$RCA_{c,p,t} = \frac{wms_{c,p,t}}{wms_{c,t}} = \frac{f\left(T_{c,p,t}, C_{c,p,t}, O_{c,p,t}\right)}{F\left(T_{c,t}, C_{c,t}, O_{c,t}\right)}.$$

It is clear from this that under competitive conditions and perfect technology diffusion as assumed in the Hecksher-Ohlin type frameworks the terms T and O would vanish. RCAs are thus only a measure of competitiveness for identical technological levels and under perfect competitive conditions. If technology is very persistent, then RCAs capture intranational intrasectoral differences in performance.

As shown in Box 2.4 world market shares $wms_{c,p,t}$ of product $p$ in country $c$ at time $t$ are a function of technological advantage, $T_{c,p,t}$, relative costs (e.g. labour costs), $C_{c,p,t}$, and specific forms of industrial organisation such as the market structure or the intensity of intrasectoral competition, $O_{c,p,t}$. It is therefore necessary to specify an empirical model that controls for all these aspects in order to be able to correctly estimate the impact of local capabilities and untraded interdependencies on competitiveness.

### 2.4.2. Estimation approach and empirical model

*Estimation approach*

The dependent variables are bounded between 0 and 1. Papke and Wooldridge (1996) propose for this type of variables using a fractional logit model which can be extended to panel data (see Box 2.5). This dynamic panel approach frequently used in this report requires including time averages of all independent variables and the initial condition (i.e. the dependent variable at time t=0). The time averages and the initial condition model individual unit effects which are assumed to be random in line with the approach proposed by Mundlak (1978) applied and adapted to the current non-linear framework by Wooldridge (2005) and Papke and Wooldridge (2008). These unit effects account for the dependence of unit effects and the explanatory variables, and in doing so they model also individual heterogeneity and therefore account for cross-sectional variation. At the same time the inclusion of the time averages allows estimating the effect of the explanatory variables holding time averages fixed, which amounts to effects resulting from variation of the explanatory variable within the units. Hence, the time averages of the independent variables represent long-run effects as they model essentially the effects of cross sectional variation on the dependent variable, whereas the quantitative variables given the inclusion of the time averages model essentially the effects of variation within units and therefore can be interpreted as short run effects.

Given the persistence of specialisation indicators dynamic panel models are estimated. In addition, given that for some regression specifications the indicators for knowledge capabilities are more highly aggregated (country vs. sector or product level) than the dependent and other independent variables the Moulton bias and serial correlation in the errors have to be taken into account and hence clustered standard errors have been used.

**Box 2.5 Using a dynamic fractional logit model to explain standardised RCAs and world market shares**

In the analysis in this section the principal dependent variable will be world market shares WMS of country c in a product class p. In later chapters the same method will be applied to standardised RCAs. These dependent variables are both bounded between 0 and 1. These bounds are not due to censoring, but are due to the construction of the variables. For this type of data Papke and Wooldridge (1996) have suggested to model the share equation using a fractional logit model. In Papke and Wooldridge (2008) they have extended this approach to panel data,

(F13) $$\mathrm{E}(y_{c,p,t} \mid x_{c,p,t}, c_{c,p}) = \mathrm{G}(x_{c,p,t}\beta + c_{c,p}),$$

where $y_{c,p,t}$ is a share variable, $x_{c,p,t}$ and β are the vectors of strictly exogenous explanatory variables and coefficients, and c, p and t are the relevant panel dimensions. Function G(·) is non-linear satisfying that the predicted variables will lie in the interval [0, 1]. Variable $c_{c,p}$ stands for unobserved individual heterogeneity. If these unit effects are random then the individual heterogeneity $c_p$ depends on the explanatory variables as follows:

(F14) $$c_{c,p} | (x_{c,p,1}, x_{c,p,2}, \dots, x_{c,p,T}) = \varphi + \bar{x}_{c,p}\xi + a_{c,p},\ a_{c,p} \sim N(0, \sigma^2{}_a),$$

where $\bar{x}_{c,p}$is the vector of time averages, and $a_{c,p}$ is the normally distributed error with zero mean. From this specification of individual heterogeneity the fractional response function in equation (F13) can be re-written as

(F15) $$E(y_{c,p,t} \,|\, x_{c,p,t}) = G(\psi_\alpha + x_{c,p,t}\beta_a + \bar{x}_{c,p}\xi_a),$$

where the subscripts $\alpha$ indicate that $a_{c,p}$ has been integrated out and the original coefficients have been divided by the scaling factor $(1 + \sigma_a^2)^{1/2}$.

Revealed comparative advantages and world market shares tend to be very persistent over time, hence, a dynamic panel model with a lagged dependent variable should be estimated. Under the assumption of strict exogeneity of $x_{c,p,t}$, Wooldridge (2005) has proposed to specify the distribution of $c_{c,p}$conditional on $x_{c,p,t}$ and the initial values $y_{c,p,0}$ of the dependent variable in order to solve the initial condition problem in dynamic, nonlinear unobserved effects models as those used here. The individual heterogeneity specified in equation (F14) thus transforms into

(F16) $$c_{c,p} \mid (x_{c,p,1}, x_{c,p,2}, \dots, x_{c,p,T}; y_{c,p0}) = \varphi + y_{c,p0}\beta_0 + \bar{x}_{c,p}\xi + a_{c,p}, a_{c,p} \sim N(0, \sigma_a^2).$$

Integrating out $a_{c,p}$ as before formula (F15) transforms into

(F17) $$E(y_{c,p,t} \,|\, x_{c,p,t} y_{c,p,t-1}; y_{c,p0}) = G(\varphi_a + y_{c,p,t-1}\gamma_a + x_{c,p,t}\beta_a + \bar{x}_{c,p}\xi_a + y_{c,p0}\beta_{0,a})$$

The most popular link function for G(·) ensuring that the predicted variables lie in the interval [0,1] is the logistic function $G(x_{c,p,t}\beta) \equiv \frac{\exp(x_{c,p,t}\beta)}{1+\exp(x_{c,p,t}\beta)}$ Papke and Wooldridge (2008) propose to estimate the fractional response function (F15) using a pooled quasi-maximum (Bernoulli)log-likelihood function to obtain a consistent and heteroscedasticity robust estimator.

*Empirical model*

It was argued that world market shares are a function of technological advantage, relative costs, and specific forms of industrial organisation such as the market structure or the intensity of intrasectoral competition. The empirical model will therefore take into account technological advantage and control for a number of indicators capturing market structure and competition as well as costs. The empirical baseline model looks as follows:

Eq. 1: $$\mathrm{E}[\mathrm{wms}_{c,p,t}|x_{c,p,t}] = \mathrm{G}(\alpha_{c,p,t} + \gamma_0 \mathrm{wms}_{c,p,t=0} + \beta_0 \mathrm{wms}_{c,p,t-1} + \beta_1 \mathrm{DENS}_{c,p,t} + \beta_2 \mathrm{cFPI}_{c,p,t} + \beta_3 \mathrm{HERF}_{p,t} + + \beta_4 \mathrm{GLI}_{c,p,t} + \beta_5 \mathrm{MS}_{p,t} + \beta_6 \mathrm{SMP}_{c,p,t} + \gamma_1 \overline{\mathrm{DENS}}_{c,p} + \gamma_2 \overline{\mathrm{cFPI}}_{c,p} + \gamma_3 \overline{\mathrm{HERF}}_{p} + \gamma_4 \overline{\mathrm{GLI}}_{c,p} + + \gamma_5 \overline{\mathrm{MS}}_{p} + \gamma_6 \overline{\mathrm{SMP}}_{c,p} + \textstyle\sum_t \lambda_t \mathrm{d}_t + \sum_c \lambda_c \mathrm{d}_c + \sum_s \lambda_s \mathrm{d}_s),$$

where $\alpha_{c,p,t}$ is the usual constant. As the estimation is through quasi maximum likelihood no error term is included in the specification. The variables with parameters $\gamma_x$ capture individual effects, and the overlined variables time averages. Technological advantage is captured through the neighbourhood density indicator (DENS) and some alternative models include also product sophistication (SOPH) as an explanatory variable. The lagged dependent variable $\mathrm{wms}_{c,p,t-1}$ reflects the assumption that specialisation patterns are persistent, and $\sum_t \lambda_t \mathrm{d}_t$ stands for time, $\sum_c \lambda_c \mathrm{d}_c$ for country, and $\sum_s \lambda_s \mathrm{d}_s$ for sector dummies. A detailed discussion of the methodology can be found in Box 2.5 and in Reinstaller (2015). The definition of the dependent variable (world market shares, wms), product neighbourhood density (DENS) and product sophistication (SOPH) have already been presented and discussed earlier in this chapter. The other variables included in this analysis are defined as follows:

- Herfindahl Index (HERF): In order to control for the market structure in each product class *p*, a Herfindahl-Index, $\mathrm{HERF}_{p,t} = \sum_c (\mathrm{wms}_{c,p,t})^2$, is used to measure market concentration and therefore proxy factors affecting the market structure in a product class such as different types of sunk costs. This indicator accounts also for product specific learning effects that act as barriers to entry and thus increase market concentration. Higher market concentration will by definition be associated with higher market shares. However, from a dynamic perspective it should be negatively related to market entry and changes in market shares both in the short and the long-run.
- Grubel-Lloyd Index (GLI): The Grubel-Lloyd index is a measure for inter-industry trade. It is defined as $\mathrm{GLI}_{c,p,t} = 1 - |x_{c,p,t} - m_{c,p,t}| / x_{c,p,t} + m_{c,p,t}$, where variable $m_{c,p,t}$ corresponds to the total value of imports of country c in product class *p*, and $x_{c,p,t}$ to the total value of exports of country *c* in product class *p* at time *t*. At values close to 1 the index reflects very intense intra-industry trade as the country imports almost as much of product class *p* as it exports products of this class. This implies that the traded commodities are more heterogeneous. Conversely, if the index takes on values close to zero inter-industry trade prevails and the country either just imports or exports products of class p and the traded commodities tend to be more homogeneous. At high levels of disaggregation high GLI values thus reflect monopolistic competition in a specific product class and therefore market niches in that product class. Hence, ceteris paribus, one should expect a negative relationship between the GLI and the world market shares in the short run as an increase of intraindustry trade implies an increase in market sementation and thus smaller market shares for a given product class. Industries with higher GLI index values are industries in which highly industrialised countries typically trade, hence for the EU-28 sample the expected long-run effect should be positive, as it is in these markets that EU exporters gain market shares.
- Chained Fisher price index of imports (cFPI): Relative price levels play an important role in the dynamics of world market shares. Problems of endogeneity however arise if one would regress a price index containing domestic price levels on world market shares. In an evolutionary logic of market competition market shares of a country in a market depend on price differentials of domestic prices and prices of the principal competitors. In the face of vertically differentiated markets and development differences across countries, average world prices may not be an accurate measure. For this reason prices of competitors are proxied through import prices[11]. The analysis relies on a chained Fisher price index of imports as a proxy for relative price developments. The Fisher price index is a geometric mean of a Paasche and Laspeyers index calculated on the basis of unit values. Feenstra (2004) has shown that the Laspeyres and Paasche indices are upper and lower bounds of the real price evolution hence Fisher price indices are a good approximation of real prices. Using chained indices eliminates the danger of potential Gershenkron effects in the series. Ceteris paribus an increase of import prices should be positively related to world market shares in exports obtained by domestic producers.

[11] For a more detailed discussion see appendix.

- Log market size world (MS): In order to control for the fact that it is more difficult to obtain higher market shares in large markets variable $\mathrm{MS_{p,t}} = \sum_c \mathrm{x_{c,p,t}}$ is included. Under the assumption of decreasing returns to scale market size should be negatively related to world market shares, whereas a positive sign should indicate the presence of increasing returns to scale.
- Strategic market penetration (SMP): In order to capture bilateral trading relationships and the strategic positioning of the exporters of a product class p in country c in world markets an index reflecting the structural match of the exports of a country relative to the world market for a product class in terms of market potential and market dynamics. First, a composite indicator $mpc_{p,c,t} = \sum_{v_{p,c,t} \in V} 100\left(v_{p,c,t} - \min(v_{p,t})\right)/\left(\max(v_{p,t}) - \min(v_{p,t})\right)$ with $v_{p,c,t} \in V; V = \{m_{p,c,t}, m\_gr_{p,c,t}\}$ is constructed. This indicator captures how important a country c is as an importer of product class c, with $m_{p,c,t}$ and $m\_gr_{p,c,t}$ representing the import value and the growth rate of imports (measured by a Birch Index). In order to get a measure whether country c is currently able to export into the high potential markets for a specific product a country-product indicator is calculated as follows: Using $mpc_{p,,t}$ allows calculating a weighted average over all the markets $q$ to which a country $c$ exports a product $p$, $mpc\_exp_{p,c,t} = \sum_q w_{pq,t} * mpc_{pq,t}$, with $w_{p,q,t} = x_{p,cq,t}/x_{p,c,t}$ reflecting the bilateral weights of exports from country $c$ to country $q$ (export share of country q in total exports of country c in product p). This indicator now captures the average importance of the export markets of a country in a specific product. It takes into account the export share a specific market has in the exports of country $c$ in product $p$. Calculating the market share weighted average importance of the global market for a product p as $mpc\_exp_{p,t} = \sum_c wms_{p,c,t} * mpc_{p,q,t}$ allows obtaining the indicator for strategic market penetration $smp_{c,p,t} = mpc\_exp_{p,c,t}/mpc\_exp_{p,t}$. This indicator is larger than one if the exports of a country in product class c are biased towards larger and faster growing markets, whereas a value smaller than one indicates that the exports of the country are biased towards smaller and less dynamic markets. In the regression this indicator should be positively related to the dependent variable.
- Country, time and sector dummies: Time and sector dummies are needed to control for variation over time or across sectors affecting export behaviour not taken into account by other variables. Sector dummies have been specified on the basis of NACE 4-digit sectors that have been matched to the HS classification on the basis of available HS-CPC concordance tables.

Competitiveness has been defined as a function of technological advantage , relative costs, and specific forms of industrial organisation such as the market structure or the intensity of intrasectoral competition. In the proposed empirical model variables DENS and SOPH cover aspects of technological advantage. Variable cFPI capture relative costs, and variables GLI, HERF and SMP cover aspects of industrial organisation and strategic market positioning. MS instead controls for the general market size as in larger markets it will typically be more difficult to achieve larger world market shares.

### *Correlation matrix and multicollinearity testing*

Table 2.3 presents the correlation matrix of the variables that are included in the econometric analysis. As can be seen the neighbourhood density indicator strongly correlates with the world market shares as would be expected from the descriptive evidence presented so far. Most of the variables are only weakly correlated with a few exceptions. For instance, the Grubel-Lloyd index is positively correlated with the neighbourhood density. This indicates that intra-industry trade and product relatedness are positively correlated, which seems plausible. If product relatedness positively contributes to unique competitive advantages, then this should also contribute to niche formation and more intensive trade inside industries. Market size and market concentration measured by the Herfindahl index are negatively correlated. This is also plausible as it should typically be more difficult to achieve high levels of market concentration in large markets.

| Table 2.3 Correlation matrix and multicollinearity statistics. Years 2003-2013, EU-28 countries | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | World market share, wms | Neighbour-hood density, dens | Product sophisti-cation, soph | Chained Fisher Import price index, cfpi | Grubel Lloyd index, gli | Herfindahl Index, herf | Market size, ms | Strategic market penetration, smp | VIF |
| World market share, wms | 1. | | | | | | | | 1.49 |
| Neighbourhood density, dens | 0.5234 | 1. | | | | | | | 1.58 |
| Product sophistication, soph | 0.0865 | 0.0138 | 1. | | | | | | 1.08 |
| Chained Fisher Import price index, cfpi | -0.0136 | 0.0049 | 0.0013 | 1. | | | | | 1. |
| Grubel Lloyd index, gli | 0.1304 | 0.4179 | 0.0012 | -0.0219 | 1. | | | | 1.16 |
| Herfindahl Index, herf | -0.0587 | -0.1442 | -0.1209 | 0.0061 | -0.2169 | 1. | | | 1.1 |
| Market size, ms | 0.0224 | 0.0979 | 0.0728 | 0.0561 | 0.2711 | -0.3556 | 1. | | 1.04 |
| Strategic market penetration, smp | 0.2201 | 0.1924 | 0.1055 | -0.0303 | 0.1322 | -0.1502 | 0.0083 | 1. | 1.16 |
| Mean VIF | | | | | | | | | 1.2 |

*Source: WIFO calculations*

Overall the correlation patterns do not hint at the danger of econometric results being biased due to multicollinearity between the explanatory variables. This is confirmed by the variance inflation statistics (VIF). The literature typically sees VIF factor values larger than ten (sometimes four) as indicating a high correlation between the predictor variables. For the variables used in the following regressions all values are well below two. Hence, the reported statistics indicate that the independent variables are largely uncorrelated.

## 2.4.3. Empirical results

Table 2.4 presents the results of the econometric analysis. It shows four models that differ from one another in the number of the explanatory variables included. This is to show the stability of the coefficients to the inclusion of additional controls. All reported coefficients are average partial effects. The table presents the results for the non-linear dynamic panel regressions. Therefore the lagged dependent variable and the initial condition have been included in each regression. The table presents likelihood ratio test statistics that test the validity of the dynamic panel model relative to a static panel and a pooled model. The first test statistic ($LR_{\beta_0,\gamma_0}$) reports the results of the LR test evaluating the dynamic panel specification against the alternative of an identical static panel. The second test statistic ($LR_{\gamma}$) evaluates the static panel specification against a completely unrestricted pooled GLM model. For all models the statistics indicate that the dynamic panel specification is preferred to all alternative (less or unrestricted) models. In addition the table presents also the Wald test statistics for the joint significance of the different dummies (country, time, sector) that have been included. In all instances the null of joint insignificance is rejected at high levels of significance. Hence, these dummies have been included in each of the reported regressions.

In the baseline Model 1 only the neighbourhood density (DENS) variables (contemporary and long-run) as well as the lagged dependent variable and the initial condition have been included. As can be seen from the table the marginal effect for the contemporary product relatedness indicator has by far the largest effect. It is considerably larger than the long run effect capturing individual heterogeneity across units. This is likely to be due to the inclusion of the lagged dependent variable that captures already a large part of the variation of this indicator. The marginal effect of the lagged dependent variable is also very high. This very basic model captures already 78 percent of the total variation in the sample. Unreported results show that in a simple static panel regression including only the neighbourhood density indicators the model would capture about 42 percent of total variation. This is very much in line with the correlation table reported before. Hence, this first analysis seems to confirm that product relatedness (and by implication untraded interdependencies in an economy) plays a crucial role for competitiveness.

Model 2 augments the first model by including also the indicator for product sophistication (SOPH). The average partial effects of the indicator are significant and negative. While the negative signs seem to be counterintuitive at a first glance this is no longer the case if one considers how both the neighbourhood density and the product sophistication indicators have been constructed. The former captures already to a large extent the diversity of the economy, whereas the latter combines information on the diversity of the economy and the "ubiquity" of the product. If now both indicators are included in one regression the neighbourhood density indicator picks up a large part of the variation that is due to the diversity of the economy, and the sophistication indicator captures the variation that is due to the ubiquity of the product. A high ubiquity is equivalent to a more competitive environment. Hence, negative signs should be expected for higher product sophistication scores if controlling for diversity. The marginal effects for the product sophistication scores are very small. This is largely due to the fact that this is a product indicator that takes on the same score for all countries exporting the product. For this reason, if it is included in the regression it does not capture differences across countries for the same product class. Rather it captures differences in competitiveness across product classes. The inclusion of the product sophistication score improves the power of the regression to explain the overall variation little.

**Table 2.4 Econometric results: International competitiveness at the product level in the context of international competition. Dependent variable = world market shares (wms)**

| **Model** | **QML_Flogit Estimator** | | | |
|---|---|---|---|---|
| **Dependent variable :** | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
| **World market share, wms** | APE | APE | APE | APE |
| lagged world market share, L.wms | 0.0870 *** | 0.0872 *** | 0.1415 *** | 0.1413 *** |
| world market share initial cond., $wms_{t=0}$ | 0.0231 *** | 0.0227 *** | 0.0190 *** | 0.0201 *** |
| Neighbourhood density, dens | 0.1176 *** | 0.1188 *** | 0.0879 *** | 0.0871 *** |
| Neighbourhood density (LR), dens_mean | 0.0170 *** | 0.0188 *** | 0.0465 *** | 0.0418 *** |
| Product sophistication, soph | | -0.0005 *** | -0.0002 *** | |
| Product sophistication (LR), soph | | -0.0002 *** | -0.0009 *** | |
| Chained Fisher Import price index, cfpi | | | 0.0000 | 0.0000 |
| Chained Fisher Import Price index (LR), cfpi_mean | | | 0.0001 | 0.0001 |
| Grubel Lloyd index, gli | | | -0.0005 *** | -0.0005 *** |
| Grubel Lloyd index (LR), gli_mean | | | 0.0057 *** | 0.0059 *** |
| Herfindahl Index, herf | | | -0.0122 *** | -0.0116 *** |
| Herfindahl Index (LR), herf_mean | | | -0.0054 *** | -0.0061 *** |
| Market size, ms | | | 0.0005 *** | 0.0005 *** |
| Market size (LR), ms_mean | | | -0.0009 *** | -0.0009 *** |
| Strategic market penetration, smp | | | 0.0084 *** | 0.0084 *** |
| Strategic market penetration, smp_mean | | | 0.0017 ** | 0.0017 ** |
| Time dummies | YES | YES | YES | YES |
| Sector dummies | YES | YES | YES | YES |
| Country dummies | YES | YES | YES | YES |
| Number of observations | 1,303,533 | 1,303,533 | 674,334 | 674,334 |
| Pseudo $R^2$ | 0.783 | 0.784 | 0.858 | 0.858 |
| Deviance | 10324.52 | 10301.15 | 5460.22 | 4357.3 |
| Log Pseudolikelihood | -58014.52 | -58002.83 | -38945.82 | -38955.59 |
| $LR_{\beta 0,\gamma 0}$ | 0.000 | 0.000 | 0.000 | 0.000 |
| $LR_{\gamma}$ | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test country dummies | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test sector dummies | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test time dummies | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: Coefficients represent average partial effects (APE)*
*Source: WIFO calculations*

Model 3 is the fully fledged model including all indicators related to technical advantage, relative prices and industrial organisation. All indicators with the exception of the import price indices are significant and the sign for the short and the long run effects point in plausible directions in line with the discussion earlier when the variables have been defined. The import prices in all likelihood are not significant because the indicator itself is rather volatile which is due to its construction (chaining increases volatility). The inclusion of these variables lowers the marginal effect for the contemporary product neighbourhood density, but at the same time increases its long run effect, such that in a linear combination the total partial effect of product neighbourhood density remains largely unchanged. The partial effect of the lagged dependent variable increases with the inclusion of the other variables, indicating that once one controls for different factors of industrial organisation the persistence of market shares even increases. Looking at the overall fit of the model the inclusion of the additional indicators adds only 7.5 percentage points to the overall explanatory power of the model which comes at the cost of losing almost half of the observations relative to the baseline model. Unreported sensitivity tests have shown that about half of the additional variation the augmented model is able to explain is due to the inclusion of the strategic market penetration (SMP) variable. If the exporters of a country are present in larger and faster growing foreign markets this has a positive impact also on their overall competitiveness. Model 4 finally is identical to Model 3 with the exception that the product sophistication indicator has not been included in the regression. As the results show this has little impact on the overall model fit and the estimated partial effects of all indicators.

### 2.4.4. Conclusions and implications of the empirical results for the analysis of Smart Specialisation

The econometric analysis corroborates the view that there is a close relationship between the competitive strengths a country develops in exports (and by implication also its comparative advantages) and the potential country specific learning and spillover effects from which exporters can benefit. The results confirm a considerable persistence in the world market shares countries are able to obtain at the level of disaggregated product classes, and they indicate that this persistence to a considerable extent is due to country specific external effects. This makes the export portfolio and the areas of strengths in exports of a country path dependent insofar as a positive feedback structure between existing capabilities and spillovers exists. Hence, the presence of untraded interdependencies on the one hand is a source of competitive advantage; on the other hand it can be a source of development traps in the sense that it is difficult for a country to develop new competencies and new competitive strengths out of the existing pool of capabilities.

As 3S is about the development of new competencies out of existing strengths the results presented so far are important in several ways. Firstly, they empirically confirm the importance of untraded interdependencies for the development of competitive strengths and their persistence. This indicates that in the short and medium run potentials to diversify into new fields out of existing areas of high competence will be closely related to established fields. The analysis of product relatedness may help identifying these diversification potentials. Secondly, the results suggest that in order to ensure sustained competitiveness it is necessary to broaden the scope of existing competence bases and related externalities such that diversification processes are also likely to take place in relatively more unrelated products or industries. This would help broaden the variety of exports and industrial output in the long run. The following chapters in this report will deal with this question.

Finally, the results indicate that the analyses in the following chapters can rely on the simplest specifications set out in this chapter, as the inclusion of variables capturing relative cost competitiveness and industrial organisation add little to the explanatory power of the baseline models, but come at the cost of losing a large number of observations. Their inclusion alters the magnitude and direction of the marginal effects for the neighbourhood density and the product sophistication, upon which the analyses in the following chapters will focus, in a rather limited way. Hence, the use and extension of the baseline specifications in the following chapters seems to be warranted.

## 2.5. AREAS OF STRENGTHS ACROSS MANUFACTURING SECTORS AND TECHNOLOGICAL FIELDS: DESCRIPTIVE EVIDENCE ACROSS EU COUNTRIES

This section will now present an analysis of the specialisation patterns that can be observed both at the level of NACE two-digt sectors and Key Enabling Technology (KET) fields across the EU. On the one hand, this descriptive analysis is important, because – as has been said earlier – Smart Specialisation implies the necessity of identifying areas of strengths. On the other hand, it provides evidence as to what concerns potential similarities but also differences across the EU Member States in terms of comparative and competitive advantages, which is important for the definition of well targeted policies supporting Smart Specialisation.

The evidence presented so far indicates that product relatedness is an important determinant of absolute advantages in trade. This suggests that product relatedness indicators such as the product neighbourhood density may be better specialisation indicators than standard measures of comparative advantage. The latter mostly take into account relative export achievements and thus outputs rather than local technological capabilities and untraded interdependencies between economic activities which are inputs in the development of absolute advantages. Product relatedness captures also productive interdependences that *may* lead to new comparative and competitive advantages and therefore has also to some extent a prospective value. This characteristic of the indicator will be used to analyse potential diversification patterns in the next section. For these reasons the analysis will rely on the three key indicators that have been introduced at the beginning of this chapter: standardised RCAs, product relatedness (neighbourhood density), and product sophistication (complexity).

Given the protracted effects of the economic crisis and the emergence of new, significant competitors in international trade, the chapter will also identify areas of strengths that have come under pressure in recent years across Member States. In the past decade the world market shares of the EU-28 have been falling relative to other important competitors in international trade. For the EU-28 countries this process was relatively moderate if compared to other leading economies such as the US or Japan. This development does not necessarily imply that European exports have been losing competitiveness; rather it reflects relative changes in the global composition of income, which has been rising quickly in many emerging economies over the past fifteen years. This development reflects also changes in the composition of global exports with patterns shifting towards more technology intense industries. This implies that some sectors are experiencing a decline while others are gaining market shares compensating losses of market share in the aggregate. Given the high persistence and path dependence in trade specialisations across countries this reallocation of market shares and resources is likely to affect EU Member States unevenly. In some countries existing areas of strength (i.e. sectors or technological fields with sustained comparative advantage over time) may experience this process more strongly than others. The analysis will rely on the criteria of the Macroeconomic Imbalances Procedures Scoreboard (MIPS) relative to the development of world market shares to identify these areas of strength under pressure.[12] "Areas of strengths" in what follows have been defined as product classes consistently exported with RCA over the three last periods in the data sample (i.e. 2011-2013). For every product class in this subset the analysis verifies whether the development of the world market shares has undergone a percentage change over three years of at least minus six percentage points, i.e. $\frac{wms_{p,c,t}-wms_{p,c,t-2}}{wms_{p,c,t-2}} \leq -6\%$. The results present export value weighted shares of product classes of the relative product classes by sector or technological field. It should be noted that the period 2011-2013 was in the aftermath of the economic crisis. Hence, the results may be biased by cyclical variations in income development.

### *Patterns of specialisation in the manufacturing sector across the EU-28 countries*

Figure 2.11 presents the weighted industry values for product relatedness (product neighbourhood density) in the left panel and the standardised revealed comparative advantages (srca) in the right panel for the two-digit manufacturing sectors across the EU-28 countries. The figure is a so-called heat plot which is a matrix in which each cell represents a country-sector pair. The colour represents the underlying indicator values. Dark colours present high indicator values (in the case of Figure 2.11 high degree of specialisation/comparative advantage) whereas light colours represent low indicator values. The data have been clustered using a hierarchical cluster algorithm in the two dimensions of the matrix (by country and by sector), and the tree structure on top and the side of the matrix represents the dendrogram for this clustering exercise. of In this dendrogram the branches that lie close together indicate high statistical correlation between the adjacent observations. The result is a matrix in which it is possible to identify patterns of specialisation across industries and countries. Table 2.5 (product relatedness) and Table 2.6 (srca) show the clusters identified in the respective heatplots organised by the country groups identified there. The sequence of the different country groups listed in the tables corresponds to the respective heat plots read from top to the bottom. The tables show which countries cluster in one group. Furthermore, one column shows the four most important industries in which the countries in this group are strongly specialised, and another column shows the four industries with the weakest specialisation in the country group.

The left panel of Figure 2.11 shows clear clustering patterns. In the top rows a cluster of countries (cf. Table 2.5, group 1) shows high product relatedness in industries that are generally considered to be low-tech, such as wearing and apparel, textiles, furniture, wood products, food or beverages. At the same time this group of countries shows a relatively low specialisation (with a few exceptions) in the computer/electronic/optical equipments, the machinery and equipment and the motor vehicles industries, which generally are considered to be medium-high to high-tech industries. Given that these groups of industries are poorly related in general across countries such specialisation patterns may hint at potential structural traps from which it is difficult to diversify into technologically more sophisticated productive structures.

Another quite obvious pattern in the industrial specialisation is that there is a large group of countries (consisting of groups 4, 5 and 6 in Table 2.5) that have a very weak specialisation in the leather, the textiles and the wearing and apparel industries. Similarly country groups 1 and 3 in Table 2.5 seem to have a low specialisation in the machinery and equipment, motor vehicles and also the computer/electr./optical equipments industries. Overall the countries listed on top of the figure cluster strongly in low- to medium tech industries, whereas the countries listed in the lower half are specialised in medium high- to high-tech industries. The six countries on the bottom of the table (country group 6 in Table 2.5) show a high specialisation in the chemical and pharmaceutical as well as the transport and equipment industries.

These patterns become more heterogeneous if one looks at the standardised RCA value in the right panel of Figure 2.11. Now the heatplot shows many distinct "islands". Unlike the product relatedness that captures local technological know-how and capabilities, the RCA values are potentially biased upwards in sectors or markets that have a small share in world trade as it is easier for a country to gain higher market shares in these sectors than in large markets. Therefore, this indicator potentially underrates competitive strengths in sectors that capture large shares of the world trade, such as the automitves industry. However, the specialisation patterns identified for the product relatedness and the standardised RCAs are closely correlated (r=0.65 for the country-

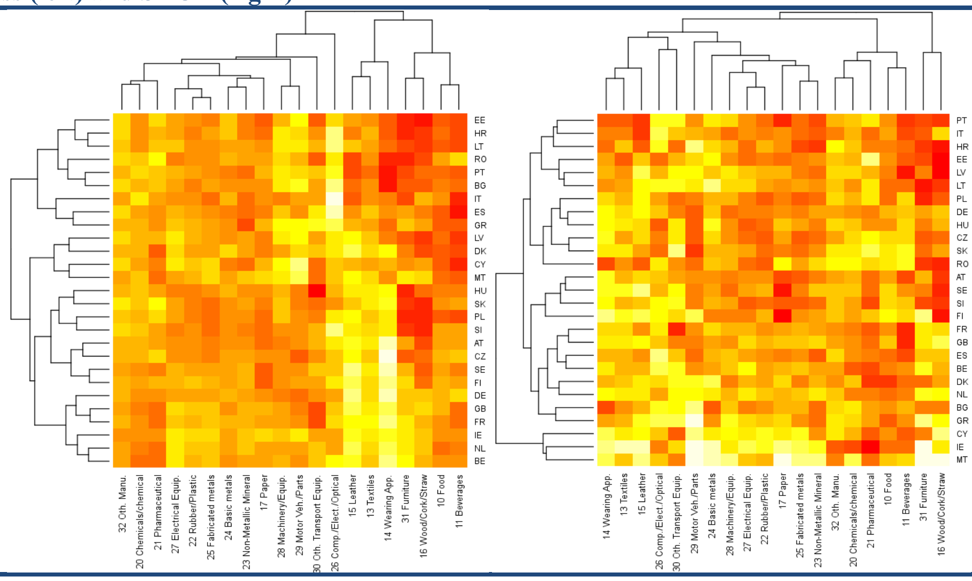
[12] http://ec.europa.eu/economy_finance/economic_governance/macroeconomic_imbalance_procedure/mip_scoreboard/index_en.htm

sector data shown in the figures).[13] For instance, the first country group in the right panel of Figure 2.11 is closely related to clusters 1 and 2 in the analysis based on product relatedness (cf. Table 2.5 and Table 2.6). Similarly, group 6 in Table 2.5 shows a similar specialisation by the same group of countries than group 4 in Table 2.6. Overall, one can conclude from the comparison that product relatedness is indeed a good measure for specialisation that shows less heterogeneity than RCAs. Given the econometric analysis at the beginning of this chapter it does however not come as a surprise that this is the case.

The analysis of the variation of sophistication of the product basket of sectors across countries shows a very clear clustering pattern, as is evident from Figure 2.12. It essentially illustrates the existence of quality ladders in terms of product sophistication scores in most industries across EU Member States. The portfolio of the countries listed in the lower half of the figure across industries the export portfolios consist of on average less sophisticated product classes than in the countries in the upper part of the figure. Table 2.7 lists the different country groups the cluster analysis has identified. The first country group consist of the countries with the on average most sophisticated product portfolios across countries, whereas country group 6 consist of the countries with the on average least sophisticated product portfolios across countries. The countries in this group have the highest sophistication scores in low tech industries like beverages, furniture or wearing apparel. The countries in country group 1 have instead the highest sophistication scores in technology intensive industries, such as machinery and equipment, pharmaceuticals or transportation equipment. Hence, they not only export in the most sophisticated product segments in each industry, but are also specialised in technologically more advanced industries.

The evidence presented so far shows that diversification happens in two dimensions. One the one hand, it is a horizontal process that affects the patterns of comparative advantages across industries in a country. On the other hand, it is a vertical process that changes the composition of the product portfolio of industries from less towards more sophisticated products. More sophisticated products involve more complex activities and therefore imply a larger number of technological competencies to draw upon. For this reason, countries that are closer to the technological frontier are typically also more competitive and specialised in more sophisticated products. This puts limits to diversification potentials.

**Figure 2.11: Specialisation patterns across industries and countries: Clustering based on product relatedness (left) and SRCA (right)**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

[13] One has to keep in mind that the two heatmaps are not directly comparable, as they order sectors and countries differently in line with the cluster analysis.

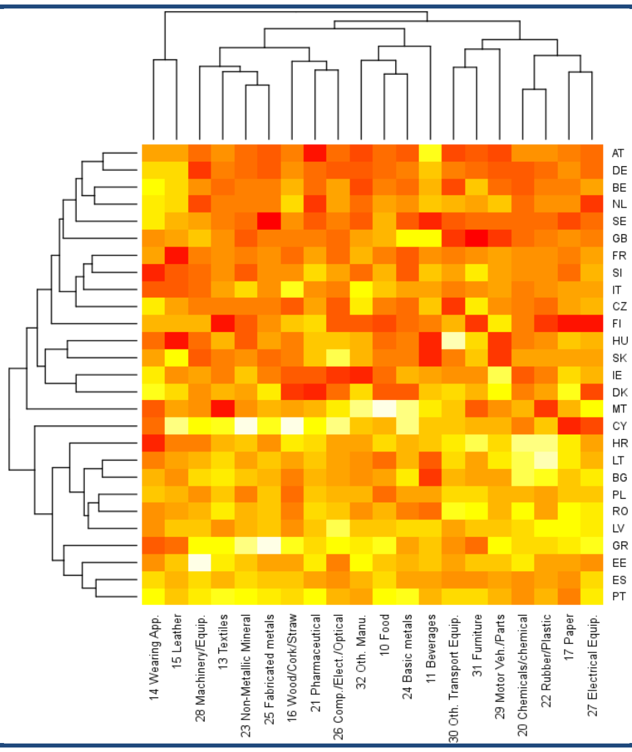
**Table 2.5: Specialization patterns across countries by product relatedness, NACE2 Sectors**

| group | countries | strongly specialised | weakly specialised |
|---|---|---|---|
| 1 | BG, EE, HR, LT, PT, RO | 14 Wearing App., 31 Furniture, 15 Leather, 16 Wood/Cork/Straw | 26 Comp./Elect./Optical, 28 Machinery/Equip., 21 Pharmaceutical, 29 Motor Veh./Parts |
| 2 | ES, GR, IT | 11 Beverages, 31 Furniture, 23 Non-Metallic Mineral, 15 Leather | 26 Comp./Elect./Optical, 20 Chemicals/chemical, 30 Oth. Transport Equip., 32 Oth. Manu. |
| 3 | CY, DK, LV, MT | 16 Wood/Cork/Straw, 11 Beverages, 21 Pharmaceutical, 10 Food | 15 Leather, 14 Wearing App., 26 Comp./Elect./Optical, 29 Motor Veh./Parts |
| 4 | HU, PL, SI, SK | 31 Furniture, 16 Wood/Cork/Straw, 11 Beverages, 10 Food | 14 Wearing App., 15 Leather, 13 Textiles, 32 Oth. Manu. |
| 5 | AT, CZ, FI, SE | 17 Paper, 16 Wood/Cork/Straw, 29 Motor Veh./Parts, 28 Machinery/Equip. | 14 Wearing App., 15 Leather, 13 Textiles, 26 Comp./Elect./Optical |
| 6 | BE, DE, FR, GB, IE, NL, LU | 30 Oth. Transport Equip., 29 Motor Veh./Parts, 21 Pharmaceutical, 20 Chemicals/chemical | 14 Wearing App., 15 Leather, 13 Textiles, 31 Furniture |

**Table 2.6: Specialisation patterns across countries by SRCAs, NACE2 Sectors**

| group | countries | strongly specialised | weakly specialised |
|---|---|---|---|
| 1 | EE, HR, IT, LT, LV, PT | 15 Leather, 11 Beverages, 16 Wood/Cork/Straw, 31 Furniture | 26 Comp./Elect./Optical, 30 Oth. Transport Equip., 20 Chemicals/chemical, 29 Motor Veh./Parts |
| 2 | CZ, DE, HU, PL, RO, SK | 29 Motor Veh./Parts, 31 Furniture, 22 Rubber/Plastic, 25 Fabricated metals | 14 Wearing App., 15 Leather, 11 Beverages, 13 Textiles |
| 3 | AT, FI, SE, SI | 17 Paper, 16 Wood/Cork/Straw, 11 Beverages, 25 Fabricated metals | 14 Wearing App., 15 Leather, 13 Textiles, 10 Food |
| 4 | BE, DK, ES, FR, GB, NL, LU | 11 Beverages, 30 Oth. Transport Equip., 21 Pharmaceutical, 10 Food | 14 Wearing App., 31 Furniture, 16 Wood/Cork/Straw, 13 Textiles |
| 5 | BG, GR | 14 Wearing App., 23 Non-Metallic Mineral, 10 Food, 24 Basic metals | 29 Motor Veh./Parts, 26 Comp./Elect./Optical, 30 Oth. Transport Equip., 32 Oth. Manu. |
| 6 | CY, IE, MT | 21 Pharmaceutical, 20 Chemicals/chemical, 32 Oth. Manu., 10 Food | 29 Motor Veh./Parts, 15 Leather, 24 Basic metals, 14 Wearing App. |

**Figure 2.12: Product sophistication patterns across industries and countries: clustering based on product sophistication scores**

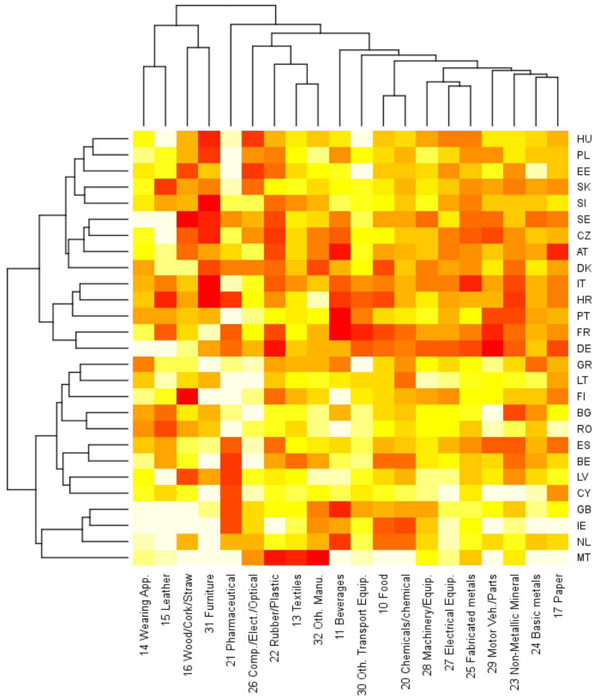



*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Table 2.7: Product sophistication patterns across countries, NACE2 Sectors**

| group | countries | highest complexity | lowest complexity |
|---|---|---|---|
| 1 | AT, BE, CZ, DE, FI, FR, GB, IT, NL, SE, SI, LU | 23 Non-Metallic Mineral, 30 Oth. Transport Equip., 26 Comp./Elect./Optical, 21 Pharmaceutical | 11 Beverages, 16 Wood/Cork/Straw, 14 Wearing App., 15 Leather |
| 2 | HU, SK | 23 Non-Metallic Mineral, 11 Beverages, 24 Basic metals, 10 Food | 30 Oth. Transport Equip., 26 Comp./Elect./Optical, 17 Paper, 21 Pharmaceutical |
| 3 | DK, IE | 16 Wood/Cork/Straw, 26 Comp./Elect./Optical, 10 Food, 32 Oth. Manu. | 17 Paper, 29 Motor Veh./Parts, 30 Oth. Transport Equip., 14 Wearing App. |
| 4 | CY | 17 Paper, 27 Electrical Equip., 14 Wearing App., 11 Beverages | 23 Non-Metallic Mineral, 24 Basic metals, 26 Comp./Elect./Optical, 13 Textiles |
| 5 | MT | 13 Textiles, 22 Rubber/Plastic, 14 Wearing App., 23 Non-Metallic Mineral | 24 Basic metals, 10 Food, 32 Oth. Manu., 30 Oth. Transport Equip. |
| 6 | BG, EE, ES, GR, HR, LT, LV, PL, PT, RO | 11 Beverages, 16 Wood/Cork/Straw, 14 Wearing App., 31 Furniture | 30 Oth. Transport Equip., 20 Chemicals/chemical, 23 Non-Metallic Mineral, 13 Textiles |

**Figure 2.13: Areas of strength under pressure, NACE2 Sectors**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Table 2.8: Clustering of areas of strength under pressure, NACE2 Sectors**

| group | countries | heavily affected | weakly affected |
|---|---|---|---|
| 1 | AT, CZ, DK, EE, HU, PL, SE, SI, SK | 31 Furniture, 16 Wood/Cork/Straw, 11 Beverages, 22 Rubber/Plastic | 15 Leather, 30 Oth. Transport Equip., 14 Wearing App., 13 Textiles |
| 2 | HR, IT, PT | 31 Furniture, 25 Fabricated metals, 11 Beverages, 23 Non-Metallic Mineral | 21 Pharmaceutical, 26 Comp./Elect./Optical, 32 Oth. Manu., 16 Wood/Cork/Straw |
| 3 | DE, FR | 29 Motor Veh./Parts, 22 Rubber/Plastic, 11 Beverages, 30 Oth. Transport Equip. | 14 Wearing App., 16 Wood/Cork/Straw, 13 Textiles, 15 Leather |
| 4 | BE, BG, CY, ES, FI, GR, LT, LV, RO, LU | 21 Pharmaceutical, 23 Non-Metallic Mineral, 20 Chemicals/chemical, 17 Paper | 26 Comp./Elect./Optical, 30 Oth. Transport Equip., 11 Beverages, 31 Furniture |
| 5 | GB, IE, NL | 11 Beverages, 21 Pharmaceutical, 20 Chemicals/chemical, 10 Food | 15 Leather, 14 Wearing App., 31 Furniture, 27 Electrical Equip. |
| 6 | MT | 32 Oth. Manu., 22 Rubber/Plastic, 13 Textiles, 26 Comp./Elect./Optical | 29 Motor Veh./Parts, 31 Furniture, 16 Wood/Cork/Straw, 17 Paper |

Figure 2.13 presents evidence relative to the exposure of the single industrial sectors to declines in world market shares. It is important to carefully interpret these data. Declines in world market shares at these high levels of aggregation can result from the fact that the export growth rates of European exporters are positive but lower than that of the general world market. This can happen, if in some sectors the market grows faster in geographically more distant regions that capture also larger shares of world trade. Here, the relative decline does not necessarily indicate a lack of competitiveness of European exports but maybe geographical or cultural barriers to deepen the presence in these markets or that growth happens largely in market segments such as low price, low quality segments that are difficult to serve by exporters from high income countries. A loss of market shares can also be related to a higher reactivity of the exports of some industries in some countries to business cycle fluctuations than that of other countries. That can be related to the specific income elasticities in the market segments where European exporters are active. Also this may not necessarily be related to a lack of international competitiveness. Globally, one can certainly say that the observed patterns have both structural and cyclical

causes. Whether they are related to poor competitiveness cannot easily be analysed at such aggregate levels of data representation as is done in this part of the study.

Returning to Figure 2.13 the results seem to support this perspective as the heterogeneity both across countries and sectors is very high and not very systematic. In several countries the rubber and plastics industry (22) and the manufacture of non-metallic mineral (23) having a high share of products exported with comparative advantage have experienced declines of more than six percentage points in world market shares between 2011 and 2013. The clustering patterns reflect national rather than industry specific patterns. Some countries like Austria, Germany or France have experienced declines in world market shares across many industries, whereas in others it was single industries that have experienced declines. Overall, the patterns seem to capture cyclical variations across countries rather than long run sorting patterns across industries. For this purpose a longer term perspective would be needed.

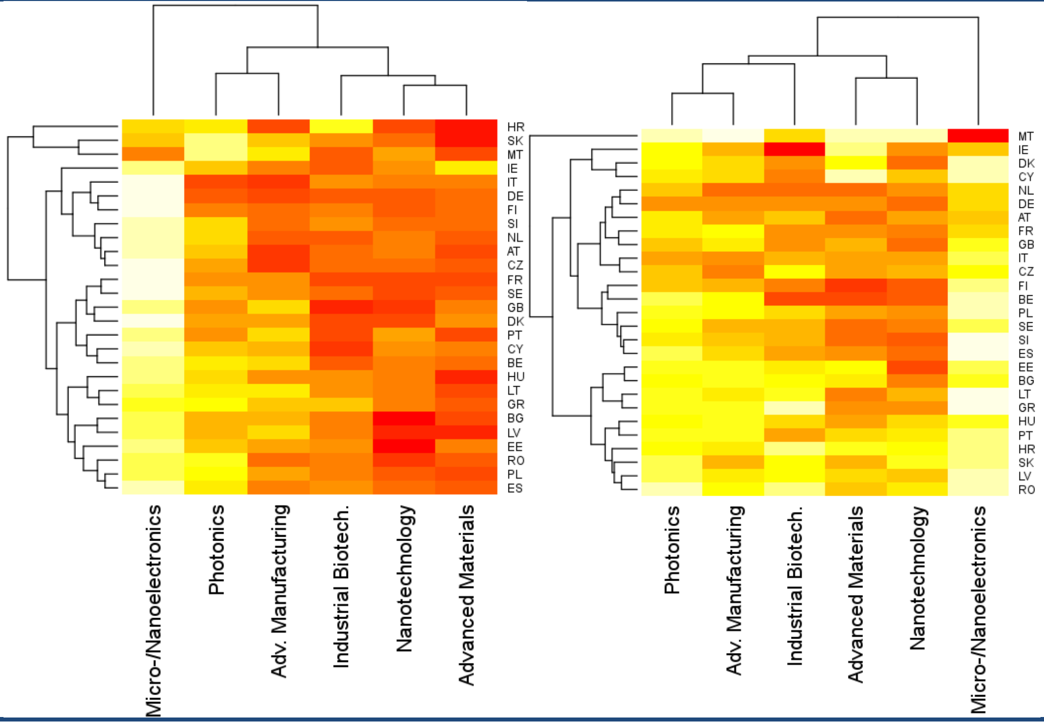
*Patterns of specialisation in Key Enabling Technology fields across the EU-28 countries*

The promotion of Key Enabling Technologies is at the centre of many EU level initiatives. Figure 2.14 through Figure 2.16 and Table 2.9 through Table 2.12 present evidence on specialisation patterns and the cross country-cross sector differences in technological sophistication across the EU countries in KETs. The structure and interpretation of the figures and tables is identical to those in the previous subsecetion.

The left panel of Figure 2.16 shows that across KET fields technological capabilities seem to be particularly pervasive across member states in the areas “advanced materials”, “nanotechnology” and “industrial biotechnology”. A generally higher specialisation in terms of product relatedness across Member States can be observed for advanced materials. In many countries these product classes are part of the productive core. However, as the table on product sophistication indicates there is great variation in terms of the sophistication of the product portfolio in this technology field as well as in terms of the comparative advantages that better capture trade intensities (see Figure 2.15). Capabilities are somewhat more concentrated in “advanced manufacturing” (see also country group 3 in Table 2.9). Just a handful of countries such as Austria, Germany, the Czech Republic, Italy or the Netherlands show a high specialisation that is reflected also in the standardised RCA scores (cf. Table 2.12). Capabilities are also rather concentrated in “photonics” even though relative to the other technological fields capabilities seem to be somewhat less pronounced. Specialisation in this field from both the product relatedness and the standardised RCA scores is relatively weak. Finally, the generally weak specialisation of European countries in the field of micro- and nanoelectronics is quite apparent from the figure. This reflects also the generally weak specialisation in the ICT industry (NACE 26, cf. Figure 2.11). The divergence of the product relatedness and SRCA patterns especially for “industrial biotechnology” may indicate that market potentials across Europe in this field may be above current achievement levels. This will be examined more in depth in the next section.

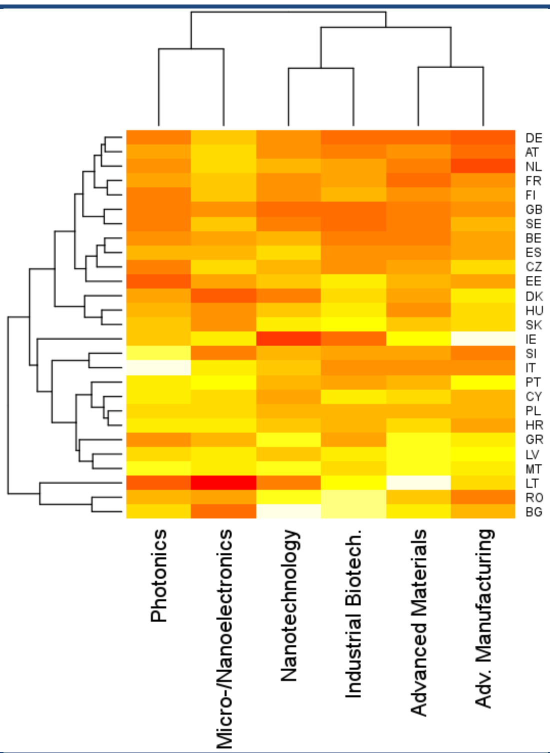
As for the manufacturing sectors Figure 2.16 presents the value weighted shares of exports and the frequency of product classes in the KETs fields that have experienced significant declines in market shares between 2011 and 2013. The data indicate that these declines have been most pronounced in the field of nanotechnology and advanced materials. Country group 1 (see Table 2.12) decline was more pronounced in “advanced manufacturing” and “photonics”, whereas in country group 5 the decline was very strong in “photonics”. Especially the decline in “photonics” is likely to be related to the fast catching up and successful market entry of Chinese producers in this field (which can benefit from large domestic markets and targeted policies). This development does not seem to be related to cyclical variations that may play a more serious role in “advanced manufacturing” and “advanced materials”. Overall the evidence in Figure 2.16 suggests that specialisation in key enabling technologies does not necessarily hedge against structural changes in international trade and a cyclical variation.

**Figure 2.14: Specialisation patterns across KET fields and countries: clustering based on product relatedness (left) and SRCA (right)**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Figure 2.15: Product sophistication patterns across KET fields and countries: clustering based on product sophistication scores**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Table 2.9: Specialisation patterns across countries by product relatedness, KET fields**

| group | countries | strongly specialised | weakly specialised |
|---|---|---|---|
| 1 | HR | Advanced Materials, Adv. Manufacturing | Industrial Biotech., Photonics |
| 2 | MT, SK | Advanced Materials, Nanotechnology | Photonics, Adv. Manufacturing |
| 3 | IE, IT, DE, FI, SI, NL, AT, CZ | Adv. Manufacturing, Nanotechnology | Micro-/Nanoelectronics, Photonics |
| 4 | FR, SE, GB, DK, PT, CY, BE, LU | Industrial Biotech., Nanotechnology | Micro-/Nanoelectronics, Adv. Manufacturing |
| 5 | HU, LT, GR, BG, LV, EE, RO, PL, ES | Advanced Materials, Nanotechnology | Micro-/Nanoelectronics, Photonics |

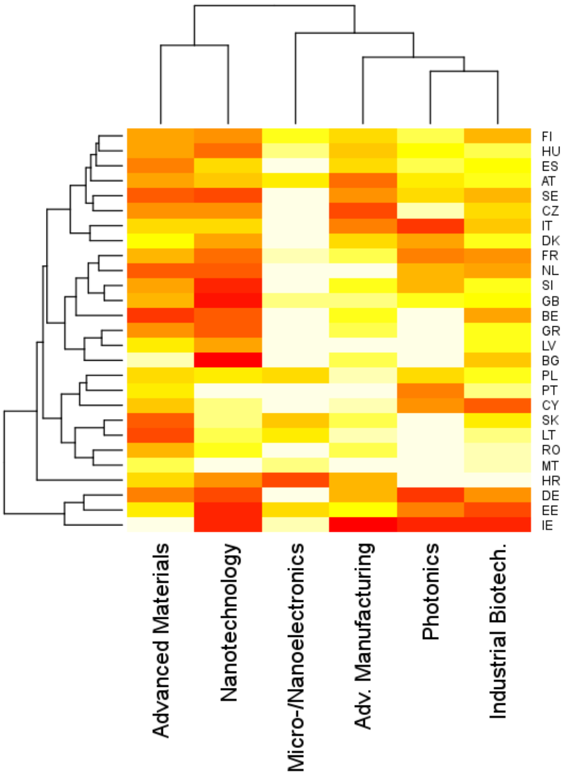
**Table 2.10: Specialisation patterns across countries by SRCAs, KET fields**

| group | countries | strongly specialised | weakly specialised |
|---|---|---|---|
| 1 | MT | Micro-/Nanoelectronics, Industrial Biotech. | Adv. Manufacturing, Photonics |
| 2 | CY, DK, IE | Industrial Biotech., Nanotechnology | Advanced Materials, Photonics |
| 3 | AT, CZ, DE, FR, GB, IT, NL | Nanotechnology, Advanced Materials | Micro-/Nanoelectronics, Photonics |
| 4 | BE, ES, FI, PL, SE, SI, LU | Advanced Materials, Nanotechnology | Micro-/Nanoelectronics, Photonics |
| 5 | BG, EE, GR, HR, HU, LT, LV, PT, RO, SK | Advanced Materials, Nanotechnology | Micro-/Nanoelectronics, Photonics |

**Table 2.11: Product sophistication patterns across countries, KET fields**

| group | countries | highest complexity | lowest complexits |
|---|---|---|---|
| 1 | AT, BE, CZ, DE, DK, EE, ES, FI, FR, GB, HU, NL, SE, SK, LU | Photonics, Advanced Materials | Industrial Biotech., Micro-/Nanoelectronics |
| 2 | IE | Nanotechnology, Industrial Biotech. | Advanced Materials, Adv. Manufacturing |
| 3 | CY, GR, HR, IT, LV, MT, PL, PT, SI | Micro-/Nanoelectronics, Adv. Manufacturing | Photonics, Nanotechnology |
| 4 | LT | Photonics, Micro-/Nanoelectronics | Advanced Materials, Industrial Biotech. |
| 5 | BG, RO | Micro-/Nanoelectronics, Adv. Manufacturing | Nanotechnology, Industrial Biotech. |

**Figure 2.16: Areas of strength under pressure, KET fields**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Table 2.12: Clustering of areas of strength under pressure, KET fields**

| group | countries | strongly affected | weakly affected |
|---|---|---|---|
| 1 | AT, CZ, DK, ES, FI, HU, IT, SE | Adv. Manufacturing, Photonics | Micro-/Nanoelectronics, Industrial Biotech. |
| 2 | BE, BG, FR, GB, GR, LV, NL, SI, LU | Nanotechnology, Advanced Materials | Micro-/Nanoelectronics, Adv. Manufacturing |
| 3 | CY, LT, MT, PL, PT, RO, SK | Advanced Materials, Photonics | Adv. Manufacturing, Micro-/Nanoelectronics |
| 4 | HR | Micro-/Nanoelectronics, Nanotechnology | Industrial Biotech., Photonics |
| 5 | DE, EE, IE | Photonics, Nanotechnology | Micro-/Nanoelectronics, Adv. Manufacturing |

## 2.6. COUNTERFACTUAL ANALYSIS OF SPECIALISATION PATTERNS IN THE EU

An important aspect of Smart Specialisation is the diversification of a given set of economic activities into new activities into technologically related fields. For Smart Specialisation policies identifying these development potentials objectively is very difficult. If the new and the old activities are too similar, i.e. when diversification happens only in technological fields that closely overlap, then learning effects will be minimal, the diversity of the knowledge base will not increase and endogenous structural change is unlikely. If on the other hand, Smart Specialisation policies promote diversification into only weakly related economic activities, this will increase the variety of knowledge in the economy, but the activities will only be weakly embedded in the economy and in the extreme case of totally incongruent knowledge bases neither benefits from nor contribute to the local knowledge base. In addition, the risk of failures increases. Hence, the question Smart Specialisation Policies have to solve is about the "optimum degree" of relatedness in order to maximise knowledge diffusion and learning while at the same time ensuring a continuous generation of new economic activities to achieve self-sustaining economic growth. Little is known about the "optimum" degree of relatedness across economic activities in an economy, and further research is needed to be able to establish this.

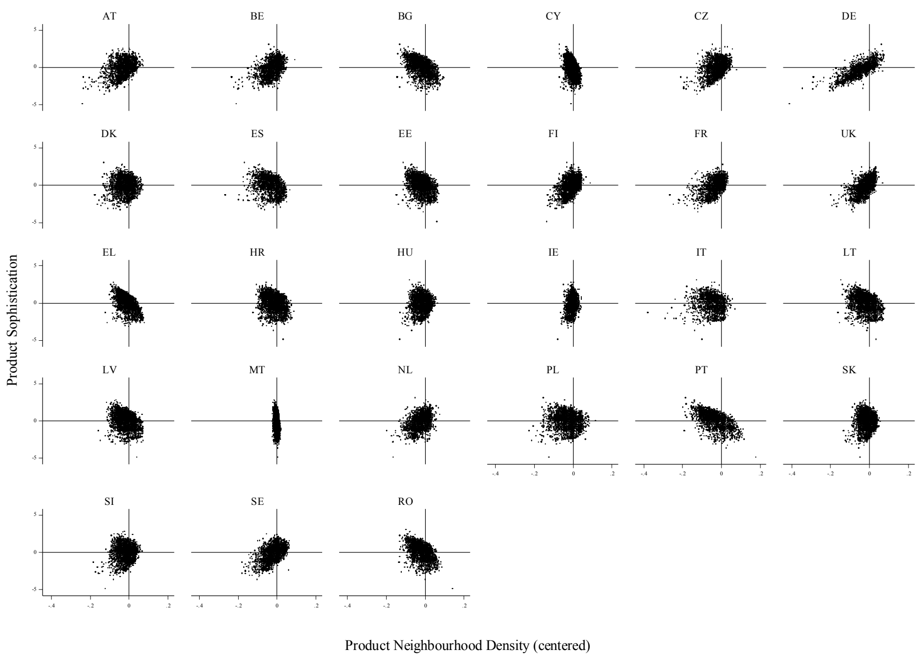
The circumstance that product relatedness has considerable power to predict both world market shares and entry into international markets of a country can be used to construct counterfactual evidence on where the EU28 countries are likely to deepen or develop new specialisations or loose them. While this analysis cannot replace more focused in-depths analyses relying on more specific data, it can be used as a device focusing attention on particularly well or badly embedded product classes and as a consequence develop better targeted diversification policies. Hence, the results presented in this part of the study do not present normative prescriptions on where EU countries should focus their diversification efforts. Rather, they should be interpreted as indicating strong or poor embeddedness of specific product classes which could potentially lead to gains (in the case of high degrees of product relatedness) or losses (in the case of low product relatedness scores) of market shares in world trade and hence to changes in the specialisation patterns of EU countries.

This is illustrated in Figure 2.17. It plots the neighbourhood density of the product classes the EU-28 countries do not export or export without comparative advantage against the product sophistication score. As can be seen from the figure many of these products are distant from the productive core of the economies as measured by the product relatedness indicator. However, it also shows that a number of products are relatively close to the productive core of each country in the sense that their product neighbourhood density score is higher than the country average (represented by the vertical line). Given the evidence presented in the previous sections one should expect that these product classes could particularly benefit from knowledge spillovers and specific competences of the country. Some of these products could therefore develop comparative advantages, and are therefore unexploited opportunities for further diversification of a country taking into account their product characteristics and the international competitive environment.

Some caveats apply, of course. There are many products in Figure 2.17 that are likely to represent a potential for increasing the trade volume and develop comparative advantages, but it may also contain non-competitive products. One should be aware on the one hand that for more larger and competitive countries the pool of products that can make this transition may be relatively small, whereas for smaller countries or countries with lower levels of achieved competitiveness the pool may be larger. Finally, there will be some "turbulence" in the sense, that a country may still export products with comparative advantage, but given for instance general market conditions or the development of general competences in the country it may be likely to lose comparative advantage in some products. This needs to be taken into account when considering the development of specialisations over time. For this reason the aim of the exercise presented here is not to develop guidelines with regard to which types of products should be supported by policy action. Indeed, the reasons for products not having captured large world market shares may be manifold and in order to derive concrete policy guidelines each product should be examined separately for each sector and country or region, which is beyond the scope of this study. The more limited aim here is to examine whether the exploitation of export potentials will tend to deepen or weaken existing specialisations.

The criteria by which potential gains and losses in trade have been identified are based on an in-sample prediction using econometric Model 3 in Section 2.4.3. The econometric model is thus used to predict the world market shares each product class should obtain given its relatedness to other products in the economy and its competitive environment. Under the assumption that in the last year in the sample the global trade volume in each industry is constant and that whatever market share the EU countries gain or lose in a product class will translate into equivalent market losses or gains in the rest of the world this prediction is used to estimate trade changes in the trade volumes in each sector or technology field. These estimated gains or losses are then translated into changes in the export shares of each country. Figure 2.18 and Figure 2.19 therefore show in which sectors or technological fields of the EU-28 countries the econometric model would predict an increase (dark shaded fields) or decrease (light shaded fields) of the export volume and hence towards which specialisation patterns the composition of the export basket of each country could potentially develop.

**Figure 2.17: Product sophistication for product classes not exported or exported without comparative advantage, EU-28 countries.**



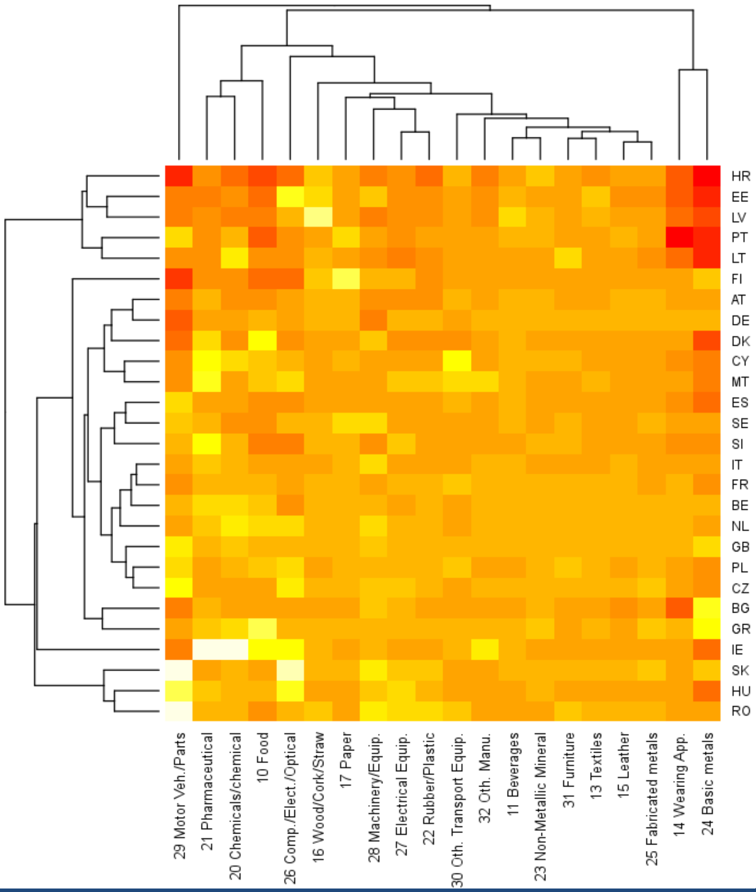

*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

Figure 2.18 and Table 2.13 show the potential gains and losses in trade for the manufacturing sector across EU countries in a clustered heatplot. The results show a relatively heterogeneous pattern. There is a large group of countries for which the results indicate potential increases in the motor vehicle, transportation equipment, basic metals and machinery and equipment sectors (country group 4 in Table 2.13). A comparison with the earlier results shows that many of these countries are already specialised in these sectors. Hence, the prediction is that the comparative advantages and the importance of these sectors are likely to increase further. Existing specialisations deepen. The same holds true for country groups 1 and 2, where starting from the current specialisation the most important predicted specialisation potentials are identified for a number of low tech industries. While at a first glance this would hint at potential low-tech development traps, a close look at the figure shows that the model would predict also increases in the chemical and the transportation equipment industries. Strengthening the technological capabilities of these sectors in these countries may therefore be a potential way out of potential development traps. Finally, country group 6 shows a remarkable result: The countries in this group have been a target for considerable inward foreign direct investment in the automotives industry. However, the results indicate that they are likely to lose exports in exactly this sector. While this may not happen, this prediction is the result of an apparently weak embedding of this industry in the ecology of the local production and innovation systems. Hence, the results would suggest that efforts should be made in these countries to strengthen the linkages of this industry.

Looking at the results for Key Enabling Technologies (KETs) in Figure 2.19 reveals that for given specialisations and technological competencies European countries should potentially be able to deepen their market shares in advanced materials, nanotechnology and industrial biotechnology. It does not come as a surprise that for most countries a deepening in micro- and nanoelectronics seems unlikely given current capabilities. It is surprising, that despite the strengths of some countries in advanced manufacturing (e.g. Germany, Austria etc) the estimations predict potential losses in market shares.

Overall, the model predictions point at and confirm a considerable persistency in development patterns. While diversification into technologically related economic activities are an important ingredient of Smart Specialisation Strategies, the results clearly show that generally, given the nature of technological search, diversification will happen into technologically related fields. The key challenge is indeed how to broaden the scope of technological search without losing the benefits of spillovers from locally developed capabilities as outlined at the beginning of this section.

**Figure 2.18: Potential gains and losses in international trade , NACE2 Sectors**

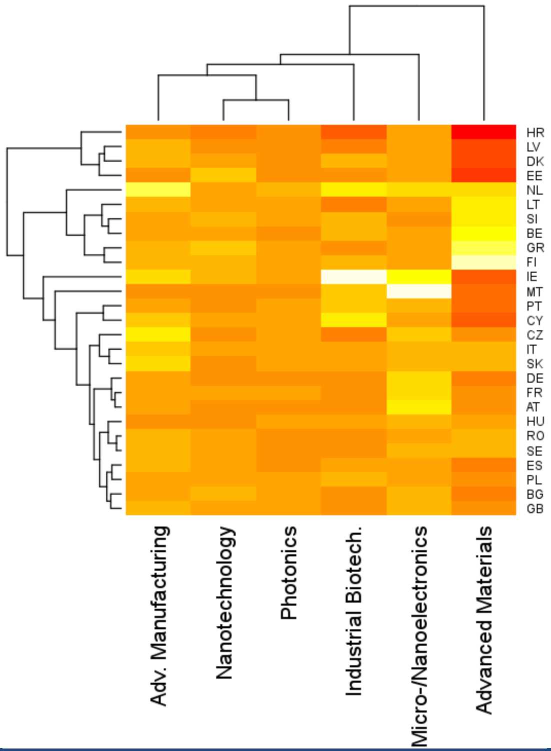



*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Table 2.13: Potential gains and losses in international trade by Country Groups, NACE2 Sectors**

| group | countries | potential increase | potential decrease |
|---|---|---|---|
| 1 | EE, HR, LV | 24 Basic metals, 14 Wearing App., 10 Food, 29 Motor Veh./Parts | 16 Wood/Cork/Straw, 26 Comp./Elect./Optical, 11 Beverages, 23 Non-Metallic Mineral |
| 2 | LT, PT | 14 Wearing App., 24 Basic metals, 10 Food, 27 Electrical Equip. | 17 Paper, 29 Motor Veh./Parts, 20 Chemicals/chemical, 31 Furniture |
| 3 | FI | 29 Motor Veh./Parts, 10 Food, 26 Comp./Elect./Optical, 21 Pharmaceutical | 17 Paper, 16 Wood/Cork/Straw, 24 Basic metals, 28 Machinery/Equip. |
| 4 | AT, BE, BG, CY, CZ, DE, DK, ES, FR, GB, GR, IT, MT, NL, PL, SE, SI, LU | 29 Motor Veh./Parts, 24 Basic metals, 28 Machinery/Equip., Transp. equipment | 10 Food, 21 Pharmaceutical, 20 Chemicals/chemical, 26 Comp./Elect./Optical |
| 5 | IE | 24 Basic metals, 29 Motor Veh./Parts, 27 Electrical Equip., 25 Fabricated metals | 21 Pharmaceutical, 20 Chemicals/chemical, 10 Food, 26 Comp./Elect./Optical |
| 6 | HU, RO, SK | 32 Oth. Manu., 14 Wearing App., 10 Food, 11 Beverages | 29 Motor Veh./Parts, 26 Comp./Elect./Optical, 28 Machinery/Equip., 27 Electrical Equip. |

**Figure 2.19: Potential gains and losses, Key Enabling Technologies**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Table 2.14: Potential gains and losses by Country Groups, Key Enabling Technologies**

| group | countries | potential increase | potential decrease |
|---|---|---|---|
| 1 | DK, EE, HR, LV | Advanced Materials, Photonics | Industrial Biotech., Nanotechnology |
| 2 | BE, FI, GR, LT, NL, SI, LU | Nanotechnology, Photonics | Adv. Manufacturing, Advanced Materials |
| 3 | IE | Advanced Materials, Photonics | Industrial Biotech., Micro-/Nanoelectronics |
| 4 | MT | Advanced Materials, Adv. Manufacturing | Micro-/Nanoelectronics, Industrial Biotech. |
| 5 | AT, BG, CY, CZ, DE, ES, FR, GB, HU, IT, PL, PT, RO, SE, SK | Advanced Materials, Industrial Biotech. | Micro-/Nanoelectronics, Adv. Manufacturing |

## 2.7. SUMMARY AND CONCLUSIONS

Empirical evidence presented in this chapter shows that industrial structures and related patterns of comparative advantages in trade are highly persistent over time across EU-28 countries, even though a more dynamical development can be observed in the EU-13 countries over the past decade. This evidence holds for highly disaggregated product classes as much as for entire sectors. The econometric analysis in this chapter indicates that this persistence is to a considerable extent due to local technological capabilities that have accumulated over time and country specific untraded interdependencies such as knowledge spillovers between different domains of the domestic knowledge base.

In line with these findings the chapter provides also evidence that new comparative advantages in trade and export potentials are likely to emerge in activities that are related to existing areas of strengths. The likely reason for this observation is that these activities can benefit from and potentially are also a manifestation of local externalities, if, for instance, the transmission channel are company spin-offs that rely on a well established knowledge base inherited from their parent companies. Comparative advantages in a country therefore tend to cluster in interrelated industries, as an analysis of specialization patterns across the EU-28 countries shows. Furthermore, these clusters of interrelated industries cluster also in specific groups of countries in the EU-28. Hence, this first set of results of the study provides evidence supporting the view that the specialisation patterns and competitive strengths of a country or a region show properties of path dependent processes, insofar as positive feedbacks between knowledge generating and knowledge using activities across specific industries and technologies exist that mutually strengthen the local knowledge base over time, beget new feedbacks and thus ensure sustained international competitiveness in the related economic and technological activities. This evidence also supports arguments in favour of public intervention to boost diversification processes presented earlier, as it indicates that the underlying technological search is indeed fairly close to existing core-capabilities of the business sector of an economy.

# Chapter 3.

# NATIONAL CAPABILITIES AND THE DETERMINANTS OF INDUSTRIAL DIVERSIFICATION

The previous chapter has discussed the role local capabilities for specialisation patterns and the development of areas of strength. The chapter has shown that local capabilities are a key predictor for competitive and comparative advantage but they are also a source for path dependency in industry structures. The purpose of chapter 3 is to analyse the relationship between national capabilities to generate and apply knowledge and the development of comparative advantages and changes in industrial specialisation at the national level. The chapter therefore investigates potential options to escape existing paths of specialisation, in particular if they are unfavourable in terms of competitiveness.

## 3.1. KNOWLEDGE CAPABILITIES TO GENERATE AND ABSORB KNOWLEDGE

Human capital theory predicts strong relationships between education and growth. Knowledge capabilities are key elements of successful innovation and therefore also a precondition for potential transitions of a country's industry structure into the production of less familiar products. Knowledge capabilities might increase both the innovation and imitation performance either by higher creativity or improved absorption of already existing knowledge. In principle, it might be assumed that those countries with high levels of education and skills are more likely to either boost already existing comparative advantage or to develop new strengths and therefore overcome path dependency in their product portfolio. However, empirical studies have had some difficulty in uncovering a significant relationship between changes in aggregate education levels and economic growth indicating that education by itself is not sufficient. It has to be transformed into productive knowledge to be applied at the workplace, whereas its application at the workplace also reinforces the applied skills via learning by doing (Kim and Nelson 2000; Lall 2001).

Furthermore, Hanushek and Woessmann (2012) have argued that the creation of human capital rather depends on a purely quantitative expansion of education in terms of years of schooling but is determined by the quality of the education people have been exposed to. It therefore would be preferable to explore whether and to what extent both quantitative and qualitative changes in human capital can affect specialization and diversification patterns in production of the EU Member States. However, data on the quality of education and skills are rare, in particular when trying to compare a broad set of countries or regions. For education quality, the study relies in a first exploratory section on the estimates of cognitive skill derived from the results of international standardized mathematics and science tests administered to 15-year olds by Hanushek and Woessmann (2012). However, the data are only available at the country level for 2003 and therefore do not show any variation over time. The indicator is therefore not usable for panel regressions. Due to the lack of other indicators on the quality of education and skills the analyses have to focus on the quantitative dimension only.

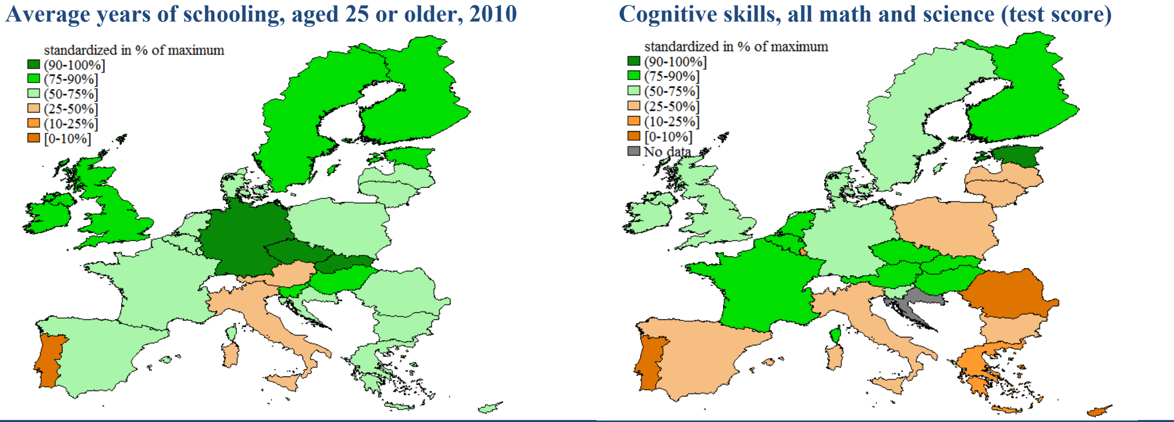
The quantity of education in the workforce is approximated using average years of schooling, and primary, secondary and college attainment rates in the population aged 15 and above (Barro and Lee 2013). Assuming tertiary education playing an important role for the development of new specialization patterns, the age group 25 years or older is used in order to avoid differences across countries due to the fact that young people are still in education. These data series are only available at the country level in 5 years intervals. In order to have the information on a yearly basis the data are interpolated and also extrapolated to the year 2012. Furthermore information on the share of human resources in science and technology is used (in various definitions, see Table 3.1 for details). The selection of these indicators was based on two tasks they have to fulfil: first, the geographical coverage of these indicators has to render possible either comparison at the country level incl. non-EU countries and at the regional NUTS2 level in order to render possible a comparison of the analyses of chapter 3 and 4. Second, the indicators have to vary over time. Otherwise they could not be used in the panel regressions.

**Table 3.1 Education, skills, knowledge generation and knowledge inflows. Overview of data sources and indicators used in the study**

| | Source | Coverage | | Level of disaggregation | | Remarks |
|---|---|---|---|---|---|---|
| | | Countries | Years | Sectors/Products | Regions | |
| **Skills and Education** | | | | | | |
| Cognitive Skills | Hanushek & Wössmann | World | 2003 | | | Cognitive skills, all math and science (test score) |
| Share of top-performing students | Hanushek & Wössmann | World | 2003 | | | Share of top-performing students |
| Average Years of Schooling | Barro & Lee | World | 2000, 2005, 2010 | - | - | population aged 25 or older, interpolated |
| Primary Attainment | Barro & Lee | World | 2000, 2005, 2010 | - | - | Share of population (aged 25 or older), interpolated |
| Secondary Attainment | Barro & Lee | World | 2000, 2005, 2010 | - | - | Share of population (aged 25 or older), interpolated |
| Tertiary Attainment | Barro & Lee | World | 2000, 2005, 2010 | - | - | Share of population (aged 25 or older), interpolated |
| Tertiary Attainment | Eurostat | EU28 | 2003-2012 | - | NUTS2 | Share of total population, interpolated |
| Early School Leavers | Eurostat | EU28 | 2003-2012 | - | NUTS2 | Share of total population, interpolated |
| Persons with tertiary education OR employed in science/tech | Eurostat | EU28 | 2003-2012 | - | NUTS2 | Share of active population |
| Persons with tertiary education AND employed in science/tech | Eurostat | EU28 | 2003-2012 | - | NUTS2 | Share of active population |
| Persons with tertiary education | Eurostat | EU28 | 2003-2012 | - | NUTS2 | Share of active population |
| Persons employed in science/tech | Eurostat | EU28 | 2003-2012 | - | NUTS2 | Share of active population |
| Persons with tertiary education OR employed in science/tech | Eurostat | EU28 | 2003-2012 | NACE 1-dig | NUTS2 | Share of total employment |
| Persons with tertiary education AND employed in science/tech | Eurostat | EU28 | 2003-2012 | NACE 1-dig | NUTS2 | Share of total employment |
| Persons with tertiary education | Eurostat | EU28 | 2003-2012 | NACE 1-dig | NUTS2 | Share of total employment |
| Persons employed in science/tech | Eurostat | EU28 | 2003-2012 | NACE 1-dig | NUTS2 | Share of total employment |
| **Knowledge generation** | | | | | | |
| Neighbourhood Density of Patents | OECD Regpat | EU28 | 2003-2012 | NACE 2-dig | NUTS2 | |
| **Knowledge inflows** | | | | | | |
| Employment Share of Firms under Foreign Ownership | Amadeus | EU28 | 2008-2012 | NACE 4-dig | NUTS2 | calculated for NACE 2-dig or country level only |
| Sophistication of Primary and Processed Industry Supplies and Capital Goods Imports | CEPII | EU28 | 2003-2012 | HS6 | - | country level indicator, different definitions used |
| Import Penetration | CEPII | EU28 | 2003-2012 | HS6 | - | either imports from (1) EU15 or (2) innovation leaders |

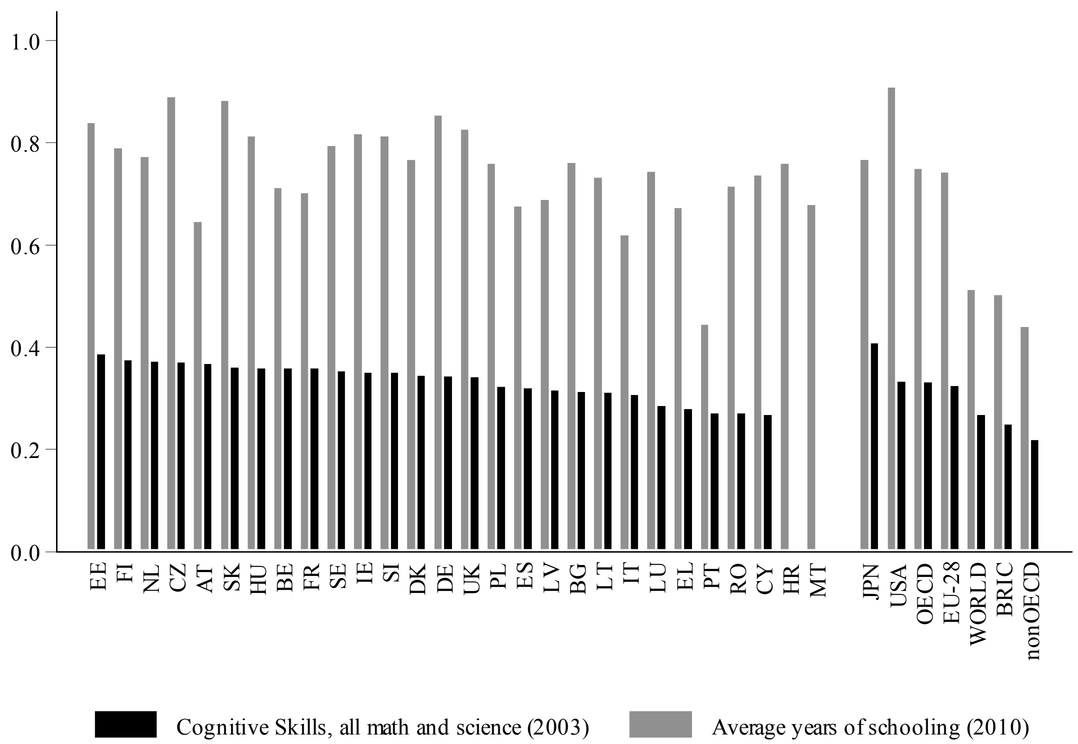
When comparing the indicators on the quantity of education with education quality indicators, some differences are observed in the performance of European countries. Figure 3.1 contrasts average years of schooling with mathematical and science test scores for the EU-28 countries. The two indicators therefore measure different aspects of education and skills and therefore difference are par for the course. For a better comparison, both indicators are standardised between 0 (minimum value over all EU-28 countries) and 1 (maximum). While some countries are ranked high (e.g. Finland or Estonia, the Czech Republic, Slovakia or Hungary) or low (e.g. Portugal or Italy) in both indicators, for some countries there exist some differences. For instance, the difference to the top performing countries in the EU is much lower for the United Kingdom, Ireland and in particular for Austria when looking at education quality instead of education quantity. On the other hand, Romania, Greece, Cyprus but also Germany show the opposite pattern.

**Figure 3.1 Qualitative vs. quantitative indicators on education and skills**




*Note: Values are standardised 0 ... minimum, 1 ... maximum in sample*
*Source: Barro and Lee (2013), Hanushek and Woessmann (2012)*

**Figure 3.2 Average years of schooling and cognitive skills, EU-28 countries and international comparison**




*Note: Cognitive skills are only available for the year 2003. Indicators are standardised between 0 (world minimum) and 1 (world maximum)*
*Source: Barro and Lee (2013); Hanushek and Woessmann (2012)*

Given these differences between qualitative and quantitative indicators, other information available from Eurostat on human resources in science and technology (HRST), early school leavers and tertiary attainment are used in order to check whether the results are robust. Various definitions for HRST are tested (see Table 3.1 for details). The advantage of these indicators is their availability at the regional level. However they are not available for non-EU countries and therefore the analyses are restricted on the EU-28 countries only. Unfortunately, none of these variables vary across industries below the NACE 1-digit level. Since the sample is restricted to manufacturing the education and skills indicators therefore do not vary within a region in the same year.

Descriptive statistics (see Table 3.2 and Figure 3.2) show that the indicator for the quantity of education varies considerably more across countries than the estimates for the quality of education. The EU-28 average for these indicators is close to the value of the OECD countries and well above that of the BRIC countries or the world at large. The number of observations per indicator in Table 3.2 is made up by the number of countries and years covered in the sample. The table shows some interesting country-specific patterns. For instance, the variation of quantitative indicators on education is quite large. This holds for the sample of covered non-EU countries, but also for the EU-28 countries. For instance, the share of persons with secondary educational attainment in total population varies between less than 20% in Malta, Portugal and Spain and more than 70% in the Czech Republic.

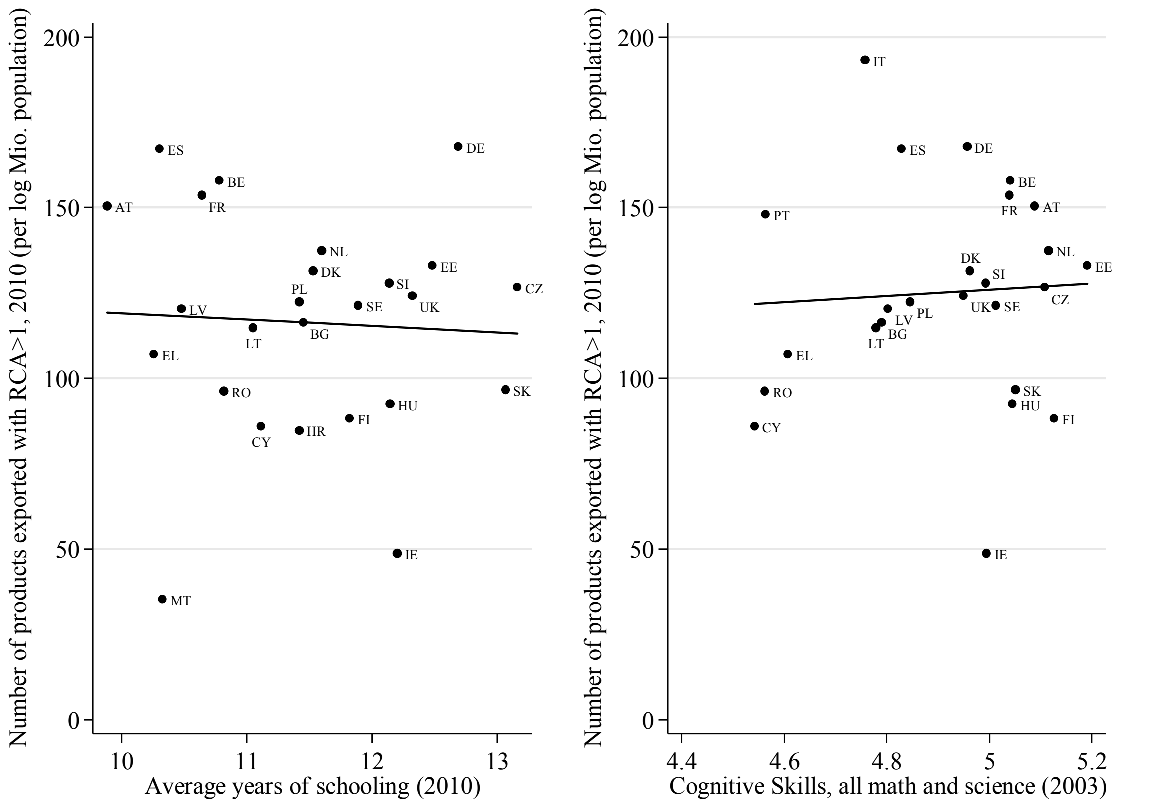
**Table 3.2 Summary Statistics - Knowledge capabilities, education and skills**

| | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| EU-28 | | | | | |
| Perc. of pop. with Primary Educ. | 270 | 12.82 | 10.07 | 0.00 | 44.26 |
| Perc. of pop. with Secondary Educ. | 270 | 40.94 | 14.93 | 11.44 | 73.00 |
| Perc. of pop. with Tertiary Educ. | 270 | 14.54 | 5.62 | 3.50 | 33.71 |
| Average Years of Schooling | 270 | 10.96 | 1.29 | 6.64 | 13.26 |
| Early School leavers in% Y18-24, Eurostat | 140 | 12.12 | 6.42 | 3.70 | 34.90 |
| Population aged 25-64 with tertiary education attainment, Eurostat | 140 | 26.52 | 8.07 | 12.80 | 39.70 |
| persons with tertiary educ. or empl. in science/tech, % of active pop | 140 | 38.48 | 7.61 | 21.50 | 56.70 |
| people with tertiary educ. AND empl in science/tech, % of active pop | 140 | 18.01 | 4.74 | 10.60 | 35.60 |
| persons with tertiary educ., in % of active pop | 140 | 27.94 | 7.73 | 14.30 | 41.50 |
| persons employed in science/tech, in % of active pop | 140 | 28.55 | 6.53 | 17.10 | 51.40 |
| persons with tertiary educ. OR empl. in science/tech, % of total empl. | 140 | 40.74 | 7.83 | 22.20 | 58.30 |
| people with tertiary educ. AND empl in science/tech, % of total empl. | 140 | 19.84 | 5.06 | 11.50 | 37.50 |
| persons with tertiary educ.,% of total empl. | 140 | 29.22 | 8.14 | 14.80 | 45.00 |
| World | | | | | |
| Perc. of pop. with Primary Educ. | 690 | 14.67 | 10.36 | 0.00 | 47.61 |
| Perc. of pop. with Secondary Educ. | 690 | 32.32 | 14.65 | 7.25 | 73.00 |
| Perc. of pop. with Tertiary Educ. | 690 | 12.96 | 7.64 | 0.16 | 38.32 |
| Average Years of Schooling | 690 | 9.69 | 2.23 | 3.58 | 14.45 |

*Source: Barro and Lee (2013); Eurostat*

Figure 3.3 plots a quantitative and a qualitative education indicator against the population adjusted number of products each of the countries has comparative advantage in. As outlined in Box 2.3, this indicator can be interpreted as a measure for the diversification of the export portfolio of a country. The figure covers EU-28 countries for the year 2010. In this simple representation the data mildly hint at a positive relationship between diversification and the quality of education in science and technology related areas in the cross section, whereas the relationship between the years of schooling seems to be slightly negative even though the regression line in the figure seems to be dominated by a few outliers[14]. However, the figure does not reveal insights into the countries' degree of specialisation, i.e. whether their revealed comparative advantages are heavily concentrated in high-end niche markets or whether they are only slightly more active in markets with large trade volumes when compared to other countries. This relationship will be examined more in depth in the regression analysis.

**Figure 3.3 Education and diversification, EU-28, 2010**




*Source: WIFO calculations. Barro and Lee (2013); Hanushek and Woessmann (2012); BACI dataset (Gaulier and Zignago 2010*

Krueger and Kumar (2004) argue that the importance of different types of knowledge capabilities and education varies with the overall growth rate of available technology. Individuals can obtain either a concept-based general education or a skill-specific vocational one. While the latter is important to absorb existing technologies, general education enables to operate and develop new production technologies. Krueger and Kumar (2004) suppose lower growth rates in equilibrium for countries focusing on vocational education when compared to countries with higher shares of general education as the latter is more important to drive technological change as well as specialisation in more technology intensive industries.

Knowledge generation is approximated by using patent data from the OECD's REGPAT database. The OECD database is based on PATSTAT which contains information on all patents applied at the European Patent Office (EPO). Patent data from the OECD include both the information on (i) technology fields and (ii) geographic origin of the invention.[15] Both is required to calculate the neighbourhood density of a country's patenting activities. The approach for calculating this indicator is similar to the product neighbourhood density described in Box 2.2. Starting point is the proximity matrix of product classes (see formula (F4) which indicates the distance between pairs of HS 6-digit product classes. This proximity matrix has been aggregated to NACE 2-digit industries in order to make it compatible with patent data. Following Van Looy, Vereyen and Schmoch (2014) technology fields defined as IPC-classes (International Patent Classification) are then assigned to NACE-2 digit industries. Unfortunately, the concordance between product classes (HS) or industries (NACE) on the one hand and technology fields (IPC) on the other hand is not available at a more disaggregated level.

The aggregated proximity matrix at the NACE 2-digit industry level is used to calculate the patent neighbourhood density following formula (F5). Analogously to product neighbourhood density, patent

[14] The left panel in Figure 3.3 excludes extreme outliers (Portugal and Italy).
[15] In this report, the patents are allocated to regions and countries based on the applicant's address.

neighbourhood density measures the average proximity of a patent to a country's current patenting activities (at the NACE 2-digit level). In other words, the patent neighbourhood density indicates how closely related the patenting activities in the respective industry are to the country's patenting activities.

While assigning patents to NACE 2-digit industry level is the only way to link patents to industries or product classes, the high level of aggregation causes some caveats. In particular, it is not possible to exactly identify whether the patenting activities that are assigned to a NACE 2-digit industry are highly related to all of the product classes within the industry. The patent indicator is therefore prone to an upward bias in the relatedness between product classes and the country's patenting activities if the patenting activities within a NACE 2-digit industry are not related to the industry's product classes a country is specialised in. Furthermore, patenting activities are more important for countries that are close to the technological frontier. For these countries, innovation activities are more important to keep up competitiveness (Acemoglu, Aghion and Zilibotti 2004). It therefore might be assumed that the relatedness of a product class to the country's patenting activities is more important for explaining specialisation patterns for the most advanced EU Member States while less important for catching-up.

**Table 3.3 Summary Statistics – Knowledge generation**

| EU-28 | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Patent neighbourhood density | 6440 | 0.35 | 0.16 | 0.00 | 0.86 |

*Source: OECD Regpat*

Table 3.3 summarises the indicator on the relatedness of patenting activities of NACE 2-digit industries within countries. The number of observations results from 23 NACE Rev.2 2-digit industries in 28 EU Member States for the time frame 2003-2012. The indicator is bounded by definition between 0 and 1. Given the higher probability of firms applying for a patent in their home country than abroad ('home country bias'), non-EU countries are less comprehensively covered in patent applications at the European Patent Office (EPO). The indicator is therefore calculated for EU-28 countries only.

Besides education, skills and innovation activities knowledge transfer is another way to build up the capabilities required to specialise in new products or to maintain comparative advantage in production. In the analyses information on FDI or imports has been used. The main data sources used are Bureau van Dijk's AMADEUS database and the BACI database from CEPII as described above in chapter 2.

The measure on FDI is based on the share of foreign owned firms in total employment. The share is calculated either for the NACE Rev. 2 2-digit level or for the country level (only for sectors B "Mining and quarrying" and C "Manufacturing" as no comprehensive information for other sectors is available due to the characteristics of the product level data used). Using Amadeus firm level data to calculate the FDI shares in employment, the main caveat is a potential bias due to the lack of representativity in these data. However, assuming that the bias is similar for all countries covered one might expect that the indicators are reliable enough for serious empirical analyses. Using Eurostat's inward FATS-statistics (foreign affiliates statistics) has also been considered. However, the FATS statistics are not usable for the analyses due to plenty of missing values causing severe bias that is not evenly distributed across countries and industries.

Indicators measuring the sophistication of (i) capital goods imports and (ii) industry supplies imports have been calculated using the categories 21 "Industrial supplies not elsewhere specified, primary", 22 "Industrial supplies not elsewhere specified, processed", 41 "Capital goods (except transport equipment)" and 42 "Capital goods (except transport equipment), parts and accessories thereof" of United Nations' (2002) classification of Broad Economic Categories. The import share of the respective products within the broad economic categories was used as a weight to calculate the average sophistication of the category (and also for all categories together) for each country. The indicators measure how sophisticated the imports within each category are for each country assuming that capital goods and industry supplies contain embodied technology that might facilitate either upgrading the productive structures or specializing into completely new fields of production.

Furthermore, the share of imports from highly developed countries has been calculated assuming that imports from these countries contain higher levels of technology than imports from less developed countries. Different definitions have been used for identifying more developed countries. For instance, the study also investigates the role of imports from (i) the innovation leaders as defined in the Innovation Union Scoreboard (incl. Germany DE, Denmark DK, Finland FI, Sweden SE and the US) or from (ii) EU-15 countries. The most important caveat for these indicators is that they ignore important determinants of trade such as geographical distance or cultural patterns.

Table 3.4 summarises the descriptive statistics for the main variables used in this chapter to approximate knowledge inflows via imports or FDI. The first two variables listed are bounded between 0 and 1 as they represent shares of foreign owned firms within the countries' manufacturing sector and NACE Rev. 2 2-digit industries. The first one does not vary within countries but over time. These indicators are not available for all countries and therefore the statistics appear only in the list of EU-28 countries. The remaining indicators show the average sophistication of capital goods (Broad Economic Categories 41 and 42) and industry supply (21 and 22) imports. Obviously, capital goods are more sophisticated than industry supplies. The table also shows that the EU-28 countries import more sophisticated capital goods and industry supplies on average, but the maxima for these indicators are found in the world sample. The former finding is due to the inclusion of catching up countries while the latter is explained by other advanced industrialized countries such as the US or Switzerland.

**Table 3.4 Summary Statistics – proxy indicators for knowledge inflows**

| | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| EU-28 | | | | | |
| Share of foreign owned companies in Country (manufacturing), Amadeus | 130 | 0.30 | 0.11 | 0.08 | 0.63 |
| Share of foreign owned companies in NACE2 per country, Amadeus | 3770 | 0.27 | 0.19 | 0.00 | 1.00 |
| Av. Sophistication of Broad Economic Category 21 Imports | 260 | -1.10 | 0.23 | -1.79 | -0.43 |
| Av. Sophistication of Broad Economic Category 22 Imports | 260 | 0.27 | 0.12 | -0.25 | 0.53 |
| Av. Sophistication of Broad Economic Category 41 Imports | 260 | 0.58 | 0.14 | 0.00 | 0.84 |
| Av. Sophistication of Broad Economic Category 42 Imports | 260 | 0.57 | 0.15 | -0.06 | 0.82 |
| World | | | | | |
| Av. Sophistication of Broad Economic Category 21 Imports | 680 | -1.23 | 0.28 | -2.20 | -0.43 |
| Av. Sophistication of Broad Economic Category 22 Imports | 680 | 0.18 | 0.20 | -0.82 | 0.54 |
| Av. Sophistication of Broad Economic Category 41 Imports | 680 | 0.57 | 0.18 | -0.30 | 1.47 |
| Av. Sophistication of Broad Economic Category 42 Imports | 680 | 0.55 | 0.15 | -0.06 | 0.82 |

*Source: Bureau van Dijk – Amadeus Database; BACI dataset (Gaulier and Zignago 2010)*

## 3.2. The relationship between specialisation, product sophistication and Knowledge Capabilities

This section presents an econometric analysis exploring the effects of knowledge capabilities and changes thereof on the development of comparative advantages and industrial specialisation.

The key hypotheses tested with this model are:

Hypothesis 1: The development of new comparative advantages in a country is positively related to the relatedness of a product to existing productive capabilities.

The first hypothesis is based on the assumption that specialising or developing comparative advantage in a product p follows path dependency. If specialising in a product requires that a country has previously developed capabilities in similar products the hypothesis is confirmed. In order to test this hypothesis accurately, the analysis will investigate whether the effect of existing capabilities in the production of related products on comparative advantage varies depending on capabilities and education. The analyses therefore also control for these variables testing hypothesis 1.

Hypothesis 2: The development of new comparative advantages in a country is decreasing with the level of sophistication of products.

The second hypothesis tackles the question whether the opportunities to develop comparative advantage in a specific product depend on the sophistication of the product. To say it differently, is it less likely that a country newly specialises in highly sophisticated than in less sophisticated products? If hypothesis 2 is rejected, specialising in new products does not depend on the characteristics (in terms of sophistication) of the product itself.

Hypothesis 3: Knowledge capabilities increase the likelihood to develop new comparative advantages in a country.

The third hypothesis is based on the assumption that education and skills reduce path dependency in developing comparative advantage in new products. If education and skills accelerate overcoming lack in capabilities, a country is more likely to specialise in products that are more distant to its previous product portfolio. This hypothesis focuses on skills and knowledge that are directly related to the product where a new comparative advantage is developed.

Hypothesis 4: Knowledge capabilities allow escaping from existing specialisation patterns.

In addition to the previous hypothesis, hypothesis 4 tackles the research question whether countries can overcome their specialisation patterns and whether it is possible to leapfrog from specialisation patterns with low development potential into more promising ones. The interaction between knowledge capabilities in the product and its relatedness to other products a country had already developed comparative advantage in is expected to positively influence the development of new areas of specialisation.

Hypothesis 5: Knowledge capabilities facilitate the upgrading of the product portfolio.

Furthermore, the study investigates whether knowledge capabilities help countries to intensify comparative advantage in sophisticated products. The confirmation of the last hypothesis would imply that knowledge capabilities would foster the specialisation in a specific product more strongly if this product is highly sophisticated. On the other hand, in order to develop comparative advantage in less sophisticated products, already existing capabilities in this product are less important.

Hypotheses 1–4 address research question 1 presented in the introduction of this report (see 0), how processes of export diversification and the emergence of revealed comparative advantages are related to capabilities to generate and apply knowledge at the country level and to changes in industrial specialisation. Hypotheses 4 and 5 will provide important insights with respect to research question 4, whether and how countries and regions with low development potential can leapfrog into more sophisticated areas of the product space.

### 3.2.1. Estimation design

For clarity of exposition the specialisation SPEC, the knowledge capabilities CAP and the sophistication of products SOPH are measured by a single variable. The empirical estimation follows the following equation:

Eq. 2:
$$\begin{aligned} \mathrm{E}\left[\mathrm{SPEC}_{c,p,t} \middle| x_{c,p,t}\right] = \mathrm{G}(&\alpha_{c,p,t} + \beta_0 \mathrm{SPEC}_{c,p,t-1} + \beta_1 \mathrm{DENS}_{c,p,t} + \beta_2 \mathrm{CAP}_{c,t} + \beta_3\left[\mathrm{DENS}_{c,p,t} \times \mathrm{CAP}_{c,t}\right] \\ &+ \beta_4 \mathrm{SOPH}_{c,p,t} + \beta_5\left[\mathrm{SOPH}_{c,p,t} \times \mathrm{CAP}_{c,t}\right] + \textstyle\sum_t \lambda_t \mathrm{d}_t + \sum_c \lambda_c \mathrm{d}_c + \epsilon_{c,p,t}), \end{aligned}$$

where $\alpha_{c,p,t}$ and $\epsilon_{c,p,t}$ are the usual constant and error terms, DENS stands for the product relatedness indicator, and the terms in brackets stand for interaction effects. In the equation the indices are for country c and time t. Depending on the dependent variable the analysis may be either carried out at the product level p or the sector level s (NACE 4-digits). Equation (1) is specified for a product level analysis[16]. The lagged dependent variable $\mathrm{SPEC}_{c,p,t-1}$ reflects the assumption that specialisation patterns are persistent, and $\sum_t \lambda_t \mathrm{d}_t$ stands for time and $\sum_c \lambda_c \mathrm{d}_c$ for country dummies.

[16] This chapter uses "at the country level" in order to contrast the findings with those presented in chapter 4. Since the regressions in chapter 3 are carried out at the product level (HS2002 6-digits) comparing specialisation patterns and world market shares in these product classes across countries, the analyses should not be mixed up with macroeconomic regressions for aggregated country level data.

Using the estimation equation Eq. 2, the hypotheses formulated in section 3.2 can be expressed as in Box 3.1.

**Box 3.1 Hypotheses tested in chapter 3**

Hypothesis 1: The development of new comparative advantages in a country is positively related to the relatedness of a product to other products a country produces: i.e. $\partial G(\cdot)/\partial DENS_{c,p,t-1} > 0$ which is equivalent to $\beta_1 > 0$ for any given level of $CAP_{c,p,t-1}$.

Hypothesis 2: The development of new comparative advantages in a country is decreasing with the level of sophistication of products, i.e. $\partial G(\cdot)/\partial SOPH_{p,t-1} < 0$, or $\beta_4 < 0$, for any given level of $CAP_{c,p,t-1}$.

Hypothesis 3: Knowledge capabilities increase the likelihood to develop new comparative advantages in a country, i.e. $\partial G(\cdot)/\partial CAP_{c,p,t-1} > 0$, or $\beta_2 > 0$, for any given level of $DENS_{c,p,t-1}$.

Hypothesis 4: Knowledge capabilities allow escaping from existing specialisation patterns, i.e. $\partial^2 G(\cdot)/\partial DENS_{c,p,t-1}\,\partial CAP_{c,p,t-1} < 0$, or $\beta_3 < 0$.

Hypothesis 5: Knowledge capabilities facilitate the upgrading of the product portfolio, i.e. $\partial^2 G(\cdot)/\partial SOPH_{p,t-1}\,\partial CAP_{c,p,t-1} > 0$, or $\beta_5 > 0$.

In the analyses, the estimation of equation Eq. 2 is repeated for different indicators. Following Achen's (2005) guideline ("Throwin every possible variable" won't work, neither will "rigidly adhere to just three explanatory variables and don't worry about anything else") the set of explanatory variables is restricted to the core set of indicators under investigation. Other indicators are included only one by one trying to avoid inferential errors. Furthermore, different subsamples (i.e. country groups) are estimated elaborating the relationship between the main dimensions more clearly. Given the differences in the main research questions in chapters 2 and 3, other indicators used in chapter 2 are therefore not included. However, as has also been shown in the previous chapter, neighbourhood density and the lagged dependent variable explain the largest shares of variation in the dependent variable. These variables are included in both analyses.

Furthermore, the regressions are redone by replacing single variables by a vector of indicators, for instance using average years of schooling (SCH) and other variables measuring education for knowledge capabilities (CAP). The indicators DENS and SOPH reflect the product space indicator on relatedness and product complexity respectively. The used right-hand side variables (RHS) are predetermined and it is therefore assumed that reverse causation is unlikely. Checking for robustness related to the characteristics of the sample of investigated countries, equation Eq. 2 is estimated for pooled data (all EU-28 countries) and for specific country groups capturing the distance to the technological frontier (cf. Reinstaller and Unterlass 2011, see section 0) in order to assess whether coefficients change significantly for different country subgroups. Redoing the analysis for single countries is not meaningful at the country level since there is no variation in the used indicators for skills and education within countries.

The estimation approach in chapter 3 follows the same fractional logit model as has been described in chapter 2 but now explaining specialisation patterns (i.e. standardised RCA values[17]). Again, the included time averages of the independent variables represent long-run effects as they model essentially the effects of cross sectional variation on the dependent variable, whereas the quantitative variables given the inclusion of the time averages model essentially the effects of variation within units and therefore can be interpreted as short run effects.

Concerns about potential endogeneity of right hand side variables can be safely discarded given the data structure. The dependent variables (standardised RCA or world market shares) are product level data measuring specialisation of countries within a product. The main indicators measuring the relatedness of a product to the countries product space (neighbourhood density) and product sophistication take into account exports of all countries in the world (for instance when calculating the proximity matrix described in (F4) required to calculate the neighbourhood density). Given the method of calculating the indicators, a causal impact of RCAs or world market shares on the independent variables is implausible. The other independent variables used are aggregated at a much higher level than product classes. It is therefore very unlikely that there is a causal relationship between specialisation patterns in a product class and the level of education for instance. Furthermore, when searching for the most adequate design for the empirical analyses system-GMM regressions have also been considered. While general test statistics suggested not to use system-GMM in this setting, test statistics on the independent variables robustly recommended to treat them as exogenous.

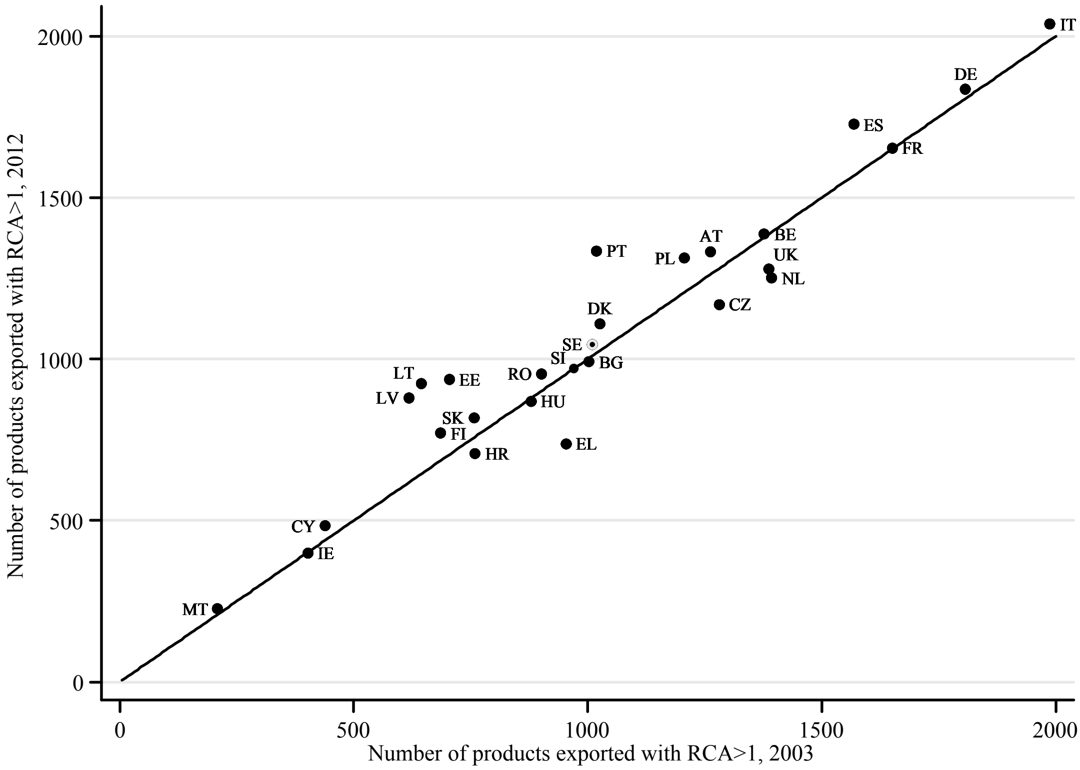
[17] The analysis of RCA values are anyway amended by explaining world market shares.

### 3.2.2. Empirical results

*Specialization patterns and the product space*

Figure 3.4 plots the number of products in which a country had a comparative advantage in 2003 against the number of products in which it had a comparative advantage in the year 2012. The aim of this figure is to illustrate the high level of persistency of diversification across countries over time. One can observe also a country size effect. Large countries export a larger number of products with comparative advantage than smaller ones as the latter on average tend to produce and export a smaller set of products.

**Figure 3.4 Persistency in the diversification of countries' product portfolio**

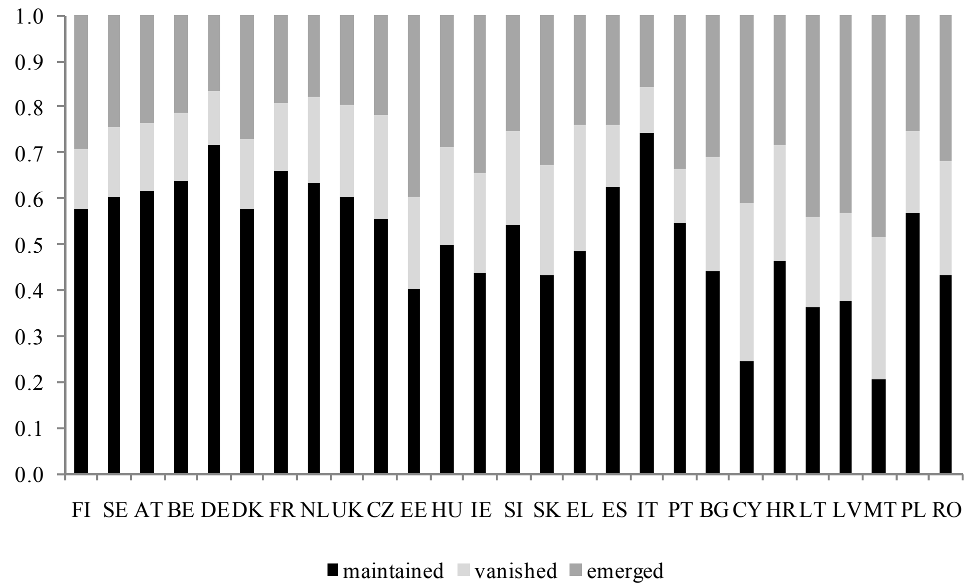



*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

Figure 3.5 shows, however, that there is considerable structural change in these data over time. While the number of products, which countries export with comparative advantage, is relatively persistent, there are many products for which countries loose comparative advantage whereas there are also many products for which they gain comparative advantage over time. The figure shows the share of products exported in the period 2010 to 2012 that have maintained their comparative advantage from the beginning, the share of products for which comparative advantage was persistently lost, and finally, the share of products for which comparative advantage was persistently gained over the observation period of ten years. These data also seem to suggest that quite different dynamics are in place in the Eastern European Member States that have experienced a massive structural change in their export portfolio, and the EU-15 countries, where the observed turnover is much less accentuated.

In the regressions highly significantly positive effects are observed for the lagged dependent variable for both samples of either EU-28 or world countries (see Table 3.5). Countries that already have a comparative advantage in a specific product in the first year are also likely to have a similar advantage in the second year. Saying it differently, having no comparative advantage in the first year will often result in a lack of comparative advantage in the second year. The regression results therefore strongly support the pattern of persistency discussed above. Restricting the sample to EU-28 countries, the estimated coefficients are even closer to unity. The same pattern holds when looking at world market shares (instead of RCA values, see Table 3.6). World market shares are very persistent over time and knowing the world market share of the previous year allows well predicting the world market shares of the following year. This result is, however, not surprising as the RCA indicator is based on ratios of world market shares.

**Figure 3.5 Structural change and the development of comparative advantages over time, by country**




*Note: Countries are sorted by country groups based on the economic and technological development as presented in Table 1.2. Graph compares shares of products in the first observed 3-year period (t-1 = 2003-2005) with the last one (t = 2010-2012), "maintained" ... RCA(t-1) > 1 & RCA(t) > 1; "vanished" ... RCA(t-1) > 1 & RCA(t) ≤ 1; "emerged" ... RCA(t-1) ≤ 1 & RCA(t) > 1*
*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

**Hypothesis 1: The development of new comparative advantages in a country is positively related to the relatedness of a product to existing productive capabilities.**

For both investigated samples of EU-28 and world countries (see Table 3.5 and Table A.17 in appendix[18]) product neighbourhood density (dens) shows highly significant coefficients in the short run indicating that the development of new fields of specialisation (i.e. products) is strongly depending on whether a country already has capabilities related to those required to produce the product[19]. On the other hand, long-run effects of product neighbourhood density are negative for RCA (dens_mean). This implies that products that score higher in product relatedness are less likely to change export status than those that have lower scores. In other words, countries already have relatively high market shares in the products they are specialised in and on average these market shares develop less dynamically[20]. It is easier to experience larger changes in RCA values from a low level (i.e. when entering a new market) than from a high level (i.e. when being established on the market) if the preconditions to enter the market are fulfilled. In order to be able to enter new fields of technology or new industries a country has to have the capabilities to do so (see Hausmann and Klinger 2006), which is reflected by the positive short run effect. In contrast, the long run effect indicates that high product relatedness limits structural adjustments of a country's export basket and induces sluggishness in the economic structure as would be expected from the literature on localised technical change and local capabilities (see e.g. Antonelli 2006, Koo 2007 or Hausmann, Hwang and Rodrik 2007). On the other hand, the result also implies that novelty from diversification into more weakly related product varieties drives the development of comparative advantages. Nevertheless, the negative long run impact is dominated by a positive short run effect such that the net effect is positive. This evidence therefore lends support to the conjecture that the probability of entry in a new international market increases with the degree of relatedness of that product to the other products exported by the country with comparative advantage[21]. However, it also shows that product relatedness tames structural adjustments. Depending on which effect dominates product relatedness may either be a source for diversification or for structural traps. The more diversified a country is the more easily it might benefit from the higher export

[18] The included indicator on tertiary educational attainment is not available for non-EU countries. Table 3.5 therefore only shows the results for the EU-28 sample.

[19] This result is in line with Schott (2004) who shows that high-wage countries use their endowment advantage to add new features to or improve quality of their varieties in order to set themselves apart from low-wage countries.

[20] This result mirrors the analysis by Ning, Prevezer and Wang (2014) which stresses the positive relationship between FDIs and the industrial diversification of regions.

[21] In Breschi, Lissoni and Malerba (2003), knowledge-relatedness is a main factor in affecting firms' technological diversification.

growth dynamics when entering new markets while a more concentrated industry structure might help gaining world market shares in industries a country is already specialised in.

The positive short run effects are even higher in the sample of EU-28 countries while for the total world sample the effects seem to be lower (see Table A.17 in appendix). The same holds for the negative long run effects, but with opposite sign. This result hints that the less developed a country, the less predetermined its productive structures are.

The estimations for world market shares confirm the results for the RCAs with the difference that now the long run effect for the neighbourhood density (dens_mean) is positive (see Table 3.6). It confirms that related capabilities have a consistent positive effect on the international competitiveness of a country, but products that are more distant to the productive structure of a country drive diversification dynamics in the long run (RCA results in Table 3.5). This supports results e.g. by Saviotti and Frenken (2008) who argue that closely related products drive export growth and export performance in the short run, while weakly related products drive performance in the long run.

All in all, neighbourhood density together with the lagged dependent variable (incl. the dependent variable in the first year) explains most of the variation of the dependent variable. The pseudo $R^2$ is mainly driven by these variables. Other variables still affect world market shares and RCA values but their explanatory power is dominated by neighbourhood density and the lagged dependent variable.

**Table 3.5 Specialisation, product space and tertiary educational attainment, product level regressions, EU-28 countries, dependent variable = standardised revealed comparative advantage (srca)**

| | Standardised revealed comparative advantage, srca | | | |
|---|---|---|---|---|
| | QML Flogit Estimator | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** |
| **EU-28 countries** | **(p-value)** | | | |
| Lagged dependent variable, (L.srca or L.wms) | 0.535 *** | +++ | +++ | +++ |
| | (0.000) | | | |
| Dep.Variable time t=0, (srcat=0 or wmst=0) | 0.114 *** | +++ | +++ | +++ |
| | (0.000) | | | |
| Neighbourhood density, dens | 1.549 *** | +++ | +++ | +++ |
| | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -1.057 *** | --- | --- | --- |
| | (0.000) | | | |
| Product sophistication, soph | 0.004 *** | +++ | +++ | +++ |
| | (0.000) | | | |
| Product sophistication (LR), soph_mean | -0.005 *** | --- | --- | --- |
| | (0.000) | | | |
| Population aged 25-64 with tertiary education, Eurostat | 0.002 *** | +++ | +++ | +++ |
| | (0.000) | | | |
| Population aged 25-64 with tertiary education, Eurostat mean | 0.164 *** | +++ | +++ | +++ |
| | (0.000) | | | |
| Interaction Neighb.density x Tertiary education | | --- | | --- |
| Interaction Neighb.density x Tertiary education (LR) | | +++ | | +++ |
| Interaction Prod. Soph. x Tertiary education | | | --- | --- |
| Interaction Prod. Soph. x Tertiary education (LR) | | | +++ | +++ |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |
| Number of observations | 910,143 | 910,143 | 910,143 | 910,143 |
| Pseudo $R^2$ | 0.828 | 0.829 | 0.828 | 0.829 |
| Deviance | 95594 | 95187 | 95521 | 95128 |
| Log Pseudolikelihood | -277831 | -277627 | -277795 | -277598 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively: ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

**Table 3.6 Specialisation, product space and knowledge capabilities, product level regressions, sample of EU-28 vs. world countries, dependent variable = world market shares (wms)**

| | EU-28 countries | | | | Pooled sample (incl. non-EU countries) | | | |
|---|---|---|---|---|---|---|---|---|
| | QML Flogit Estimator | | | | QML Flogit Estimator | | | |
| **Model** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Dependent Variable:** | APE | Sign | Sign | Sign | APE | Sign | Sign | Sign |
| **World market share, wms** | (p-value) | | | | (p-value) | | | |
| Lagged world market share, L.wms | 0.092 *** | +++ | +++ | +++ | 0.074 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| World market share time t=0, $wms_{t=0}$ | 0.020 *** | +++ | +++ | +++ | 0.019 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 0.113 *** | +++ | +++ | +++ | 0.097 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | 0.017 *** | +++ | +++ | +++ | 0.012 *** | +++ | -- | +++ |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication, soph | -0.000 ** | +++ | -- | +++ | -0.000 *** | +++ | 0 | +++ |
| | (0.018) | | | | (0.001) | | | |
| Product sophistication (LR), soph_mean | 0.000 | +++ | + | +++ | 0.000 *** | +++ | +++ | +++ |
| | (0.121) | | | | (0.000) | | | |
| Average years of schooling, sch | 0.000 *** | +++ | +++ | +++ | 0.001 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Average years of schooling (LR), sch_mean | 0.022 *** | +++ | +++ | +++ | 0.013 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Interaction Neighb.density x Av. Years of schooling | | --- | --- | | | --- | --- | |
| Interaction Neighb.density x Av. Years of schooling (LR) | | --- | --- | | | 0 | +++ | |
| Interaction Prod. Soph. x Av. Years of schooling | | --- | | --- | | --- | | --- |
| Interaction Prod. Soph. x Av. Years of schooling (LR) | | --- | | --- | | --- | | --- |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 3,209,121 | 3,209,121 | 3,209,121 | 3,209,121 |
| Pseudo $R^2$ | 0.796 | 0.801 | 0.800 | 0.798 | 0.790 | 0.792 | 0.790 | 0.791 |
| Deviance | 9771 | 9586 | 9663 | 9693 | 31382 | 31053 | 31366 | 31087 |
| Log Pseudolikelihood | -55227 | -55134 | -55188 | -55173 | -124733 | -124568 | -124725 | -124586 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

**Hypothesis 2: The development of new comparative advantages in a country is decreasing with the level of sophistication of products.**

A significant and negative long-run impact of product sophistication (soph_mean) on comparative advantages is found for both the pooled (world) sample and the sample of EU countries (see Table 3.5 and Table A.17 in appendix). This indicates that the more complex a product is, the less likely countries are able to specialise in this product as it requires higher levels of capabilities. For the pooled sample (incl. non-EU countries) the effect is less robust (see Table A.17 in appendix). Therefore, the relationship between product sophistication and comparative advantage is more complex. In the short run, product sophistication (soph) is positively correlated with higher RCA values and the effect is much higher when restricting the sample to EU-28 countries. Comparing specialisation patterns within EU-28 countries shows that these countries are more likely to develop comparative advantages in more complex products, as despite the high variation of economic performance and technological sophistication across EU Member States, the majority of them are advanced industrialised countries. However, this is not the case for all countries included in the pooled sample. For developing countries it is easier to specialise in less complex products because they can compensate their disadvantage of low levels of education with low wage costs (see e.g. Schott 2004)[22]. In OLS and random fixed effects regressions (results not presented here) this pattern appears even more clearly. In the pooled sample the sign of product sophistication is negative, while within the sample of EU-28 countries it is positive. However, these regressions do not distinguish between short and long run effects and are less adequate for the type of data used in this analysis.

**Table 3.7 Specialisation, product space and knowledge capabilities, product level regressions by groups of EU Member States, dependent variable = Standardised revealed comparative advantage (SRCA)**

| | Country Groups | | | |
|---|---|---|---|---|
| | QML Flogit Estimator | | | |
| | Groups 1&2 | Group 3 | Group 4 | Group 5 |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** |
| **Dependent Variable:** | **APE** | **APE** | **APE** | **APE** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | **(p-value)** | **(p-value)** | **(p-value)** |
| Lagged standardised revealed comparative advantage L.srca | 0.623 *** | 0.395 *** | 0.525 *** | 0.380 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.141 *** | 0.081 *** | 0.119 *** | 0.065 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Neighbourhood density, dens | 1.350 *** | 2.123 *** | 1.477 *** | 1.898 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Neighbourhood density (LR), dens_mean | -0.978 *** | -0.885 *** | -0.574 *** | -0.804 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Product sophistication, soph | -0.008 *** | 0.009 *** | 0.020 *** | 0.027 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Product sophistication (LR), soph_mean | 0.005 *** | -0.003 *** | -0.006 *** | -0.008 *** |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| Average years of schooling, sch | 0.008 *** | -0.004 *** | 0.063 *** | 0.042 *** |
| | (0.000) | (0.002) | (0.000) | (0.000) |
| Average years of schooling (LR), sch_mean | 0.488 *** | 0.818 *** | 0.943 *** | 0.964 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |
| Number of observations | 418,581 | 325,563 | 186,036 | 325,563 |
| Pseudo $R^2$ | 0.868 | 0.78 | 0.844 | 0.781 |
| Deviance | 27410 | 43627 | 17258 | 46897 |
| Log Pseudolikelihood | -143199 | -83890 | -62526 | -81245 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses*
*Source: WIFO calculations*

Breaking down the analysis for the EU-28 countries into different country groups organised by their differences in the stage of technological and economic development as described in Table 1.2, earlier results presented in Table 3.5 and Table 3.6 are confirmed. Those EU countries close to the technological frontier are more likely to be specialised in sophisticated products than, for instance, the EU-13 countries. Table 3.7 shows that the long run effect of product sophistication (soph_mean) is positive for the pooled sample of country groups 1 & 2 (see

[22] For a further discussion about poor countries having troubles developing more competitive exports see Hidalgo et al. (2007).

column (1) on the left)[23] representing frontier countries. For the remaining country groups which represent countries with different degrees of innovativeness and economic development the long run effect is negative. Furthermore, the larger the distance to the frontier the higher is the negative long-run effect. The short run effects (soph) show the opposite sign weakening the long run effect. However, the variation of the product sophistication indicator over time (within a product) is much lower than the difference in the long-run average sophistication across products.

The results for world market shares show that they tend to increase with a product's sophistication. This pattern is reflected by the positive sign in the long run effect (soph_mean). In the short run, product sophistication (soph) is negatively correlated with world market shares when neglecting potential interaction effects between product sophistication and education (see Table 3.6, column (1) for the EU-28 sample and (5) for the pooled sample). However, it is more difficult for a country to gain market shares the more complex a product is. Product sophistication seems to "protect" exporters of complex products from the entry of new competitors in the short run, as this requires higher levels of technical and market specific capabilities (see Etro 2007, for a detailed discussion). The regressions explaining world market shares are in line with the results described above on comparative advantage. However, average partial effects are quite small.

*Specialization patterns and the role of education and skills*

**Hypothesis 3: Knowledge capabilities increase the likelihood to develop new comparative advantages in a country.**

Table 3.8 summarises the results stemming from different regressions similar to those explained above but using a set of alternative indicators for education and skills. Given the high number of indicators explored in this exercise the table summarises the results for each tested variable from multiple regressions. Each row displays the sign of the variables' coefficients in the short run and long run (first two columns on the left), its interaction effects with neighbourhood density (two columns in the middle) and with product sophistication (two columns on the right). Since multiple regressions have been carried out, the table also takes into account if the sign or the level of significance differs across regressions.

When looking at the countries' knowledge capabilities the indicators for international competitiveness positively correlate with higher degrees of specialisation. Higher levels of education have a significant and positive effect on both performance indicators. This implies that higher levels of education promotes the development of new and the deepening of existing specialisations. By construction, the RCA indicator also includes the share in world trade of the product. Average RCA values are highest for countries if they are specialised in products with low overall trade volumes. A positive sign of the capability indicators' coefficients therefore hint at better educated countries being specialised in products that are less commonly produced (and exported). In other words, these countries tend to be specialised in niche markets. As the indicator world market shares is by definition quite similar to RCAs, a positive correlation with the education and skill indicators is also observed both in the long and the short-run. However, in the case of world market shares a positive sign of the indicators on skills does not hint at higher degrees of specialisation but rather at higher competitiveness on average. Countries with higher levels of education tend to have higher world market shares. This result is in line with previous literature pointing out that a higher level of education increases average earnings and productivity and decreases the probability of social problems that, in turn, affect economic development (e.g. Krueger and Lindahl 2000 or Psacharopoulos and Patrinos 2004).

The results described above basically hold for various other available indicators tested (see Table 3.8); the share of employees with higher (secondary and/or tertiary) education and the share of human resources in science and technology in total employment (or alternatively in active population[24]) show a positive but not always significant relationship with both RCA values and world market shares (see first two columns on the left in Table 3.8). The share of persons with primary education in total population is negatively correlated with the endogenous variables (please note the reversed scale of these two indicators in comparison to the others). Together these results confirm hypothesis 3. Knowledge capabilities are very likely to increase a country's likelihood to gain world market shares and develop new comparative advantages.

[23] The same holds for repeating the regressions for both groups separately (results not presented here).
[24] Using the share of human resources in science and technology in total employment, the results are less robust than using the same share but in active population.

**Table 3.8 Specialisation, product space and knowledge capabilities, product level regressions for EU-28 countries, alternative indicators measuring education, dependent variable = Standardised revealed comparative advantage (SRCA) or world market shares (wms)**

| | Variable | | Interaction Term - Neighbourhood Density | | Interaction Term - Product Sophistication | |
|---|---|---|---|---|---|---|
| **Standardised revealed comparative advantage, srca** | Short Run | Long Run | Short Run | Long Run | Short Run | Long Run |
| percentage of population with completed Primary Education (Barro Lee) | +/- | - | - | 0 | + | - |
| percentage of population with completed Secondary Education (Barro Lee) | +/- | + | + | (+) | - | + |
| percentage of population with completed Tertiary Education (Barro Lee) | + | + | + | +/- | - | + |
| early School leavers in% Y18-24 (Eurostat) | + | - | - | + | + | 0 |
| population aged 25-64 with tertiary education attainment (Eurostat) | + | + | - | + | - | + |
| persons with tertiary educ. or empl. in science/tech, % of active pop. | + | + | - | + | - | + |
| people with tertiary educ. AND empl in science/tech, % of active pop. | +/- | + | - | + | - | + |
| persons with tertiary educ., in % of active pop. | + | + | - | + | - | + |
| persons employed in science/tech, in % of active pop. | (+) | + | - | + | - | + |
| persons with tertiary educ. OR empl. in science/tech, % of total empl. | + | +/- | - | + | - | + |
| people with tertiary educ. AND empl in science/tech, % of total empl. | +/- | +/- | - | + | - | + |
| persons with tertiary educ., in % of total empl. | + | +/- | - | + | - | + |
| persons employed in science/tech, in % total empl. | + | +/- | - | + | - | (+) |
| **World market share, wms** | | | | | | |
| percentage of population with completed Primary Education (Barro Lee) | (-) | - | + | + | + | + |
| percentage of population with completed Secondary Education (Barro Lee) | + | (+) | (-) | - | - | - |
| percentage of population with completed Tertiary Education (Barro Lee) | + | + | + | - | 0 | - |
| early School leavers in% Y18-24 (Eurostat) | + | 0 | - | (-) | (-) | + |
| population aged 25-64 with tertiary education attainment (Eurostat) | + | 0 | - | + | - | - |
| persons with tertiary educ. or empl. in science/tech, % of active pop. | + | 0 | - | (+) | - | - |
| people with tertiary educ. AND empl in science/tech, % of active pop. | + | 0 | - | + | - | - |
| persons with tertiary educ., in % of active pop. | + | 0 | - | + | - | 0 |
| persons employed in science/tech, in % of active pop. | (+) | 0 | - | - | - | - |
| persons with tertiary educ. OR empl. in science/tech, % of total empl. | (+) | 0 | - | + | - | (+) |
| people with tertiary educ. AND empl in science/tech, % of total empl. | (+) | (+) | - | 0 | - | - |
| persons with tertiary educ., in % of total empl. | (+) | 0 | - | + | - | + |
| persons employed in science/tech, in % total empl. | (+) | 0 | - | + | - | - |

*Note: + ... robustly sign. positive coefficient in all tested equations, (+) ... positive but not always significant, - ... robustly sign. negative coefficient in all tested equations, (-) ... negative but not always significant, 0 ... neither sign. positive nor negative results, +/- contradicting significant results depending on the specified equation*
*Source: WIFO calculations*

Table 3.9 summarises the results for repeating the regressions explaining standardised RCA values by either average years of schooling or tertiary education attainment for country groups introduced in Table 1.2 differentiating between stages of economic development. The table shows that the pattern observed for the pooled sample of EU Member States is also confirmed for subsamples. The coefficients of both the long-run and short-run effects are significantly positive for almost all country groups. However, due to the smaller set of countries in the subsamples, the patterns are less robust. For a few regressions the short run effect turns significantly negative but overall the positive impact of knowledge capabilities and education on specialisation is confirmed.

**Table 3.9 Specialisation, product space and education and skills, product level regressions for different country groups, dependent variable = standardised revealed comparative advantage (srca)**

| | Variable | | Interaction Term - Neighbourhood Density | | Interaction Term - Product Sophistication | |
|---|---|---|---|---|---|---|
| | Short Run | Long Run | Short Run | Long Run | Short Run | Long Run |
| Average Years of Schooling | | | | | | |
| Country Group 1 | +/- | + | - | - | (-) | - |
| Country Group 2 | + | + | - | + | +/- | - |
| Country Group 3 | +/- | + | - | + | - | + |
| Country Group 4 | + | + | - | - | - | (-) |
| Country Group 5 | + | + | - | +/- | - | + |
| Tertiary Educational Attainment | | | | | | |
| Country Group 1 | (+) | + | + | + | (+) | (+) |
| Country Group 2 | + | + | - | + | +/- | +/- |
| Country Group 3 | + | + | + | + | - | + |
| Country Group 4 | + | 0 | - | + | (-) | (+) |
| Country Group 5 | +/- | 0 | - | + | - | + |

*Note: + ... robustly sign. positive coefficient in all tested equations, (+) ... positive but not always significant, - ... robustly sign. negative coefficient in all tested equations, (-) ... negative but not always significant, 0 ... neither sign. positive nor negative results, +/- contradicting significant results depending on the specified equation*
*Source: WIFO calculations*

**Hypothesis 4: Knowledge capabilities allow escaping from existing specialisation patterns.**

Testing hypotheses 4 and 5 requires including interaction terms into the regressions. By estimating nonlinear models the analysis has to take into account that partial effects of the interacted variables also depend on the full vector of explanatory variables used (cf. Ai and Norton 2003). Furthermore, statistical tests about partial effects for interacted regressors in nonlinear models are not informative (see Greene 2010). Therefore, partial effects are not reported for the interaction terms in the tables but the estimated partial effects are plotted for the interacted variables for each observation in the sample of EU-28 countries. The graphical representation shows the magnitude of the partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted dependent variable. The tables only indicate the sign and significance of the estimated effects. Reporting average partial effects for interacted variables only without taking into account the interaction effects is not meaningful. Hence, the discussion of the results refers to average partial effects of an interacted variable taking into account also the impact of the other variable (see Box 2.1). The partial effect expressed in this way therefore reflects also the complementary effect of the interacted variables.

**Box 3.2 Interaction terms in a nonlinear model**

The inclusion of interaction terms in the regressions allows investigating how the effects of (i) neighbourhood density and (2) product sophistication on either world market shares or RCA values depend on education, skills or other indicators approximating capabilities. Thereby hypotheses about an interaction term in a nonlinear model are tested (cf. Ai and Norton 2003). The correct partial effects for the logit function in the equations (following the specification in Eq. 2) for the variables neighbourhood density and product sophistication taking into account interaction effects are then:

(F18) $$\frac{\partial \mathrm{SPEC}_{c,p,t}}{\partial \mathrm{DENS}_{p,t}} = \left(\beta_1 + \beta_3 * CAP_{c,t}\right) * \frac{e^{V_i}}{(1+e^{V_i})^2}$$

(F19) $$\frac{\partial \mathrm{SPEC}_{c,p,t}}{\partial \mathrm{SOPH}_{p,t}} = \left(\beta_4 + \beta_5 * CAP_{c,t}\right) * \frac{e^{V_i}}{(1+e^{V_i})^2}$$

where $V_i = x_i\beta$ is the vector of all explanatory variables and their respective coefficients. Clearly, these marginal effects can be nonzero and are determined by all covariates of the observation (i.e. product) even if $\beta_3 = 0$ or $\beta_5 = 0$ respectively. As statistical tests about partial effects for interacted regressors in nonlinear models are not informative (see Greene 2010), pseudo partial effects are not included for the interaction terms in the tables but their sign is indicated. In order to illustrate the partial effects of the key variables the estimated partial effects are plotted for each observation in the sample. The graphical representation shows the magnitude of the overall partial effects of one variable on the dependent variable (standardised RCA values or world market shares) taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation.

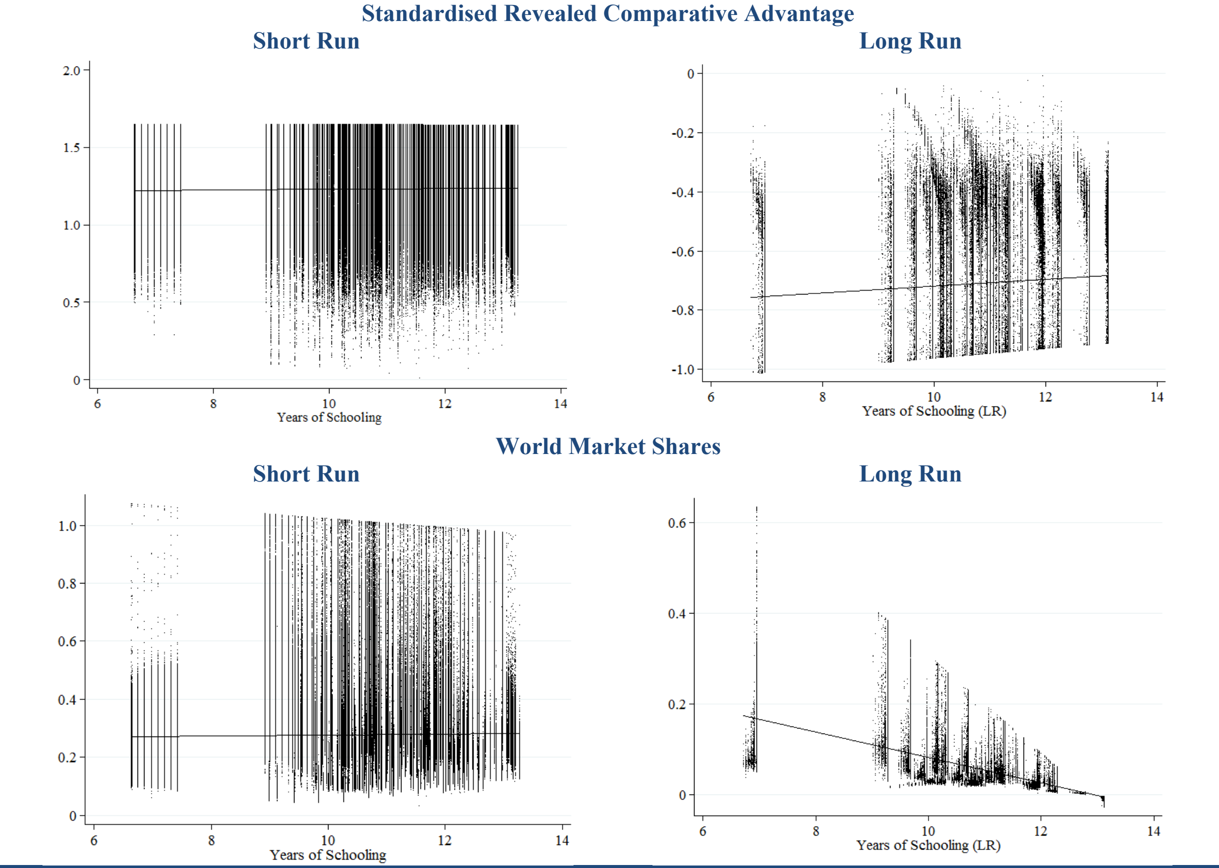
Testing hypothesis 4 requires looking at the complementary relationship between knowledge capabilities and product relatedness as captured by the product neighbourhood density. Hence, the main interest lies in the partial effects including the interaction terms for the short run and the long run. The upper left panel in Figure 3.6 shows the partial effect of the product neighbourhood density on revealed comparative advantage in the short run. On average, the effect is positive but does not significantly change with a country's average years of schooling. Thus, in the short run schooling does not affect the impact of capabilities in related technologies on the RCA value. This is plausible insofar as these related capabilities are an expression of cumulated and possible tacit knowledge, and thus formal schooling may do little to strengthen or tame the impact of related skills on RCA. However, in the long run average years of schooling reduce the negative impact of product neighbourhood density on the development of new specialisations observed before. The sluggishness in the industry structure as described above (upper right panel in Figure 3.6) decreases with average years of schooling. Using other indicators approximating education and skills the effect is significantly negative in the short run and robust with respect to previous results in the long run (see Table 3.8).

The positive effect of higher levels of education (i.e. reducing sluggishness in the industry structure) is even more clear-cut when looking at world market shares (lower panels in Figure 3.6). Schooling helps to tap into new industries and gain market shares that are more distant to a countries product space by reducing the positive impact of neighbourhood density on world market shares. The levels of market shares obtained in any product class therefore become gradually independent of capabilities in related fields thereby reducing path dependence. The figure clearly shows that education in the long run gradually eliminates the effect of related capabilities. The likely explanation for this result is that broader, more extensive competencies permit to absorb very different types of knowledge more easily thus reducing the impact of localised related knowledge approximated by neighbourhood density. Other indicators for knowledge capabilities support this finding as well. Almost all variables used in the regressions (compare columns (3) and (4) in Table 3.8) show similar patterns with regard to the sign and significance of the coefficients, but the size of the coefficients and partial effects varies.

Looking at differences across countries taking into account their stage of economic development reveals that the importance of a product's relatedness to the country's product space decreases with higher levels of education independently of the stage of economic development. In particular for the indicator average years of schooling the interaction term between neighbourhood density and education is significantly negative for all regressions (see Table 3.9). However, for the most developed countries within the EU-15 (country group 1) and the EU-13 countries (country group 3[25]) the interaction effect turns significantly positive. Since these country groups are characterised by high shares of industries classified as technology intensive, this result might hint at the importance of knowledge cumulativeness. If these industries require more skills to be specialised in, higher levels of education positively correlate with RCA values. On the contrary, in the long run the positive interaction term is found for almost all country groups but again the results are less robust than for the pooled sample.

All in all the results indicate that education helps gaining world market shares in products that are more distant to a country's product space indicating a confirmation of Hypothesis 4.

**Figure 3.6 The effect of product neighbourhood density on comparative advantage and world market shares depending on average years of schooling, sample of EU-28 countries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. Barro and Lee (2013), BACI dataset (Gaulier and Zignago 2010)*

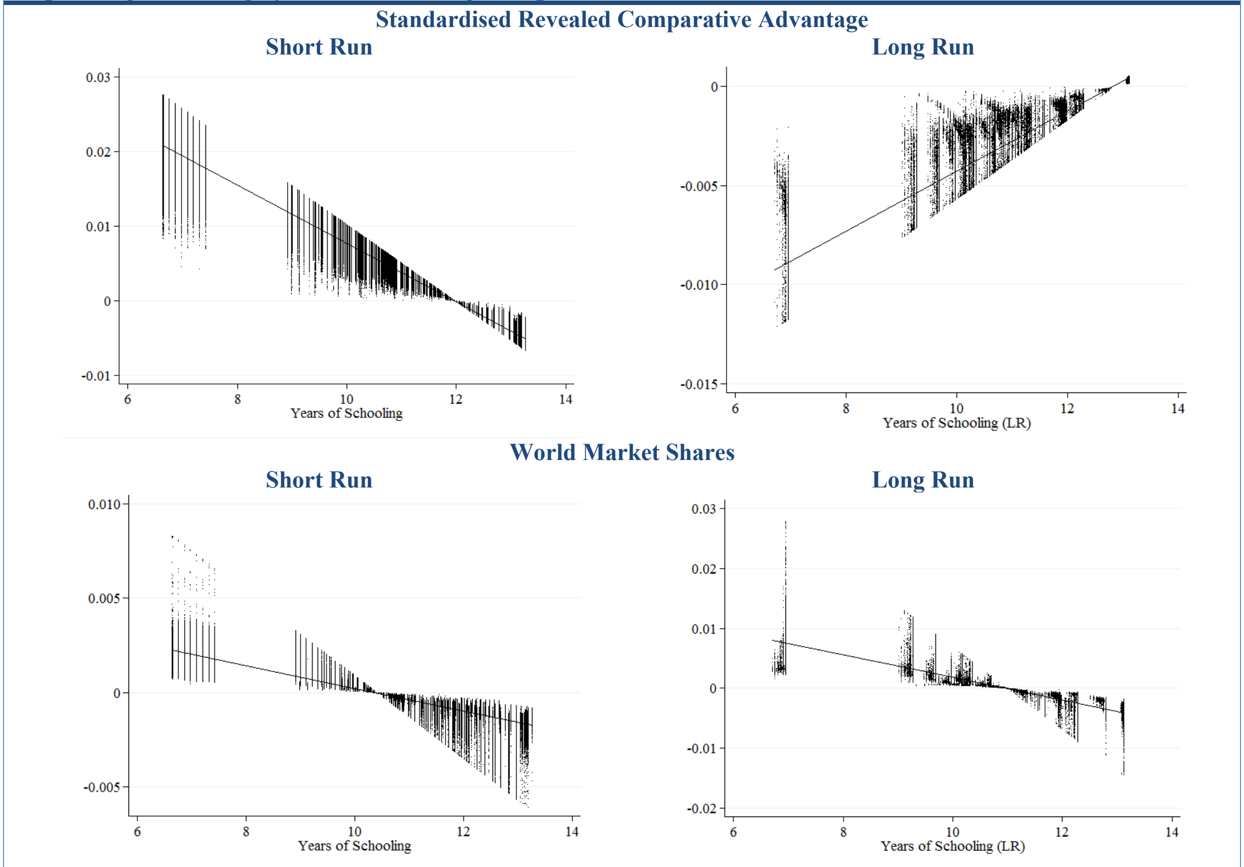
[25] incl. Ireland

**Hypothesis 5: Knowledge capabilities facilitate the upgrading of the product portfolio.**

Hypothesis 5 is explored through the examination of partial effects of product complexity scores and their interdependence with education on the specialisation and competitiveness indicators. Figure 3.7 presents the results for short and long run effects. The two panels at the left hand side shows that the positive effect of product sophistication on both world market shares and RCA values is declining with higher average years of schooling in the short run and turns negative for high average years of schooling. This effect is even higher for world market shares in the long run (lower right panel).

The interpretation of a reduction in the level of product sophistication as a result of increasing school years might appear counterintuitive. However, product sophistication is in principle determined by the breadth of the knowledge base in a country represented by its diversification. The higher its diversification the higher are also the product sophistication scores a country typically obtains. As schooling broadens the skill base, schooling also improves the development of comparative advantage in sophisticated products and therefore reduces the positive effect of sophistication on world market shares. Hence, the higher the knowledge base (as captured by the years of schooling) the less distinctive is product sophistication as a driving force of market shares and international competitiveness. This interpretation is also backed by the positive long run interaction between schooling and product sophistication when explaining RCA values. Schooling reduces the negative impact of product sophistication on RCA values (upper left panel in Figure 3.7) while in the short run any effect appears to be quite small. All in all, the results seem to confirm hypothesis 5 indicating that knowledge capabilities facilitate the upgrading of the product portfolio.

**Figure 3.7 The effect of product sophistication on comparative advantage and world market shares depending on average years of schooling, sample of EU-28 countries**




*Note : Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*

*Source: WIFO calculations. Barro and Lee (2013), BACI dataset (Gaulier and Zignago 2010)*

**Table 3.10 Specialisation, product space and knowledge generation, product level regressions, EU-28 countries and EU Member States with high direct and indirect R&D intensity, dependent variable = standardised revealed comparative advantage (srca)**

| | EU-28 countries | | | | EU Member States with high direct and indirect R&D intensity | | | |
|---|---|---|---|---|---|---|---|---|
| | | QML Flogit Estimator | | | | QML Flogit Estimator | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(1)** | **(2)** | **(3)** | **(4)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** | **APE** | **Sign** | **Sign** | **Sign** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | | | | **(p-value)** | | | |
| Lagged dependent variable, (L.srca) | 0.531 *** | +++ | +++ | +++ | 0.521 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Dep.Variable time t=0, (srcat=0) | 0.105 *** | +++ | +++ | +++ | 0.133 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 1.415 *** | +++ | +++ | +++ | 1.684 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -0.861 *** | --- | --- | --- | -1.196 *** | +++ | 0 | --- |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication, soph | 0.004 *** | +++ | +++ | +++ | -0.007 *** | --- | --- | --- |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication (LR), soph_mean | -0.004 *** | 0 | --- | 0 | 0.002 | --- | 0 | 0 |
| | (0.000) | | | | (0.307) | | | |
| Patent neighbourhood density, pat_dens | 0.001 | +++ | +++ | 0 | 0.075 *** | +++ | ++ | +++ |
| | (0.525) | | | | (0.000) | | | |
| Patent neighbourhood density (LR), pat_dens_mean | -0.137 *** | +++ | +++ | --- | -0.115 *** | +++ | +++ | --- |
| | (0.000) | | | | (0.000) | | | |
| Interaction Neighb.density x Patent neighbourhood density | | --- | --- | | | 0 | 0 | |
| Interaction Neighb.density x Patent neighbourhood density (LR) | | --- | --- | | | --- | --- | |
| Interaction Prod. Soph. x Patent neighbourhood density | | --- | | --- | | + | | ++ |
| Interaction Prod. Soph. x Patent neighbourhood density (LR) | | --- | | --- | | +++ | | + |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 1,000,593 | 1,000,593 | 1,000,593 | 1,000,593 | 74,118 | 74,118 | 74,118 | 74,118 |
| Pseudo $R^2$ | 0.825 | 0.826 | 0.826 | 0.825 | 0.875 | 0.876 | 0.876 | 0.875 |
| Deviance | 106561 | 105778 | 105850 | 106507 | 5720 | 5686 | 5699 | 5719 |
| Log Pseudolikelihood | -306576 | -306185 | -306221 | -306549 | -20980 | -20963 | -20969 | -20979 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero. 'EU Member States with high direct and indirect R&D intensity' refers to the most advanced country group as defined in Table 1.2.*
*Source: WIFO calculations*

*Specialization patterns and knowledge generation*

While education and skills are important for all stages of economic development - although the importance of different types of education (e.g. secondary vs. tertiary education) may vary (Aghion et al. 2005) - knowledge generation activities are even more important at the technological frontier. Highly developed countries base their competitive advantage mainly on high quality and more sophisticated products (Acemoglu, Aghion and Zilibotti 2004). In the analyses of the importance of knowledge generation for specialisation patterns, the study focuses on the connection between the relatedness of products countries are specialised in and the relatedness of their patenting activities. The main advantage of this approach is to consider whether existing knowledge generating (or innovation) capabilities are related to technology fields or industries a country is not specialised in yet. However, the empirical results should be interpreted with care. Due to data limitations the indicator patent neighbourhood density is aggregated at the NACE 2-digit level. This relatively high level of aggregation (compared with HS 6-digit product classes) complicates the interpretation and the results are to some degree less reliable than for the indicators on skills and education.

In general, patenting activities tend to be correlated with existing productive structures, in particular if considering that firms focus their research and therefore also their patenting activities on those technologies their products rely on. Due to the different levels of aggregation (HS 6-digit level product classes vs. IPC classes aggregated to NACE 2-digit industries) an exact correlation cannot be calculated. Including the relatedness of knowledge generation (i.e. patent neighbourhood density), the estimated effects of product sophistication and product neighbourhood density on RCA values remain unchanged at the country level (see Table 3.10). For both variables, the effects are positive in the short run and negative in the long run.

When looking at the relatedness of patenting activities (measured by patent neighbourhood density), similar patterns are observed than for product neighbourhood density. In the long run, a higher degree of relatedness of an industry to the countries patenting activities also induces sluggishness in productive structures (pat_dens_mean). This pattern is similar to the effect described above for product neighbourhood density. The effect is even more heavily driven by the fact that there exist product classes within NACE 2-digit industries the countries are not able to export although they are closely related to other products from a technological perspective. In this case, RCA values in a specific product class can be equal to zero but neighbourhood density is anyway high. In addition to the pattern described for product neighbourhood density, the sluggishness effect of patent neighbourhood density on specialisation is even higher. Due to the high level of aggregation when calculating the indicator, the relatedness of non-exported product classes to patent activities is upward biased if a country has high patenting activities in the same NACE 2-digit industry but not directly related to the non-exported product class.

On the other hand, the positive short-run effect that would have been expected from theoretical considerations (similar to the product neighbourhood density) is not found. The short-run coefficient is insignificant (pat_dens). Note that, again, the relatedness of product classes that are not exported to the country's patenting activities is overrated if patenting activities within a NACE 2-digit industry are not directly related to the product classes. This bias renders the impact of patent neighbourhood density insignificant.

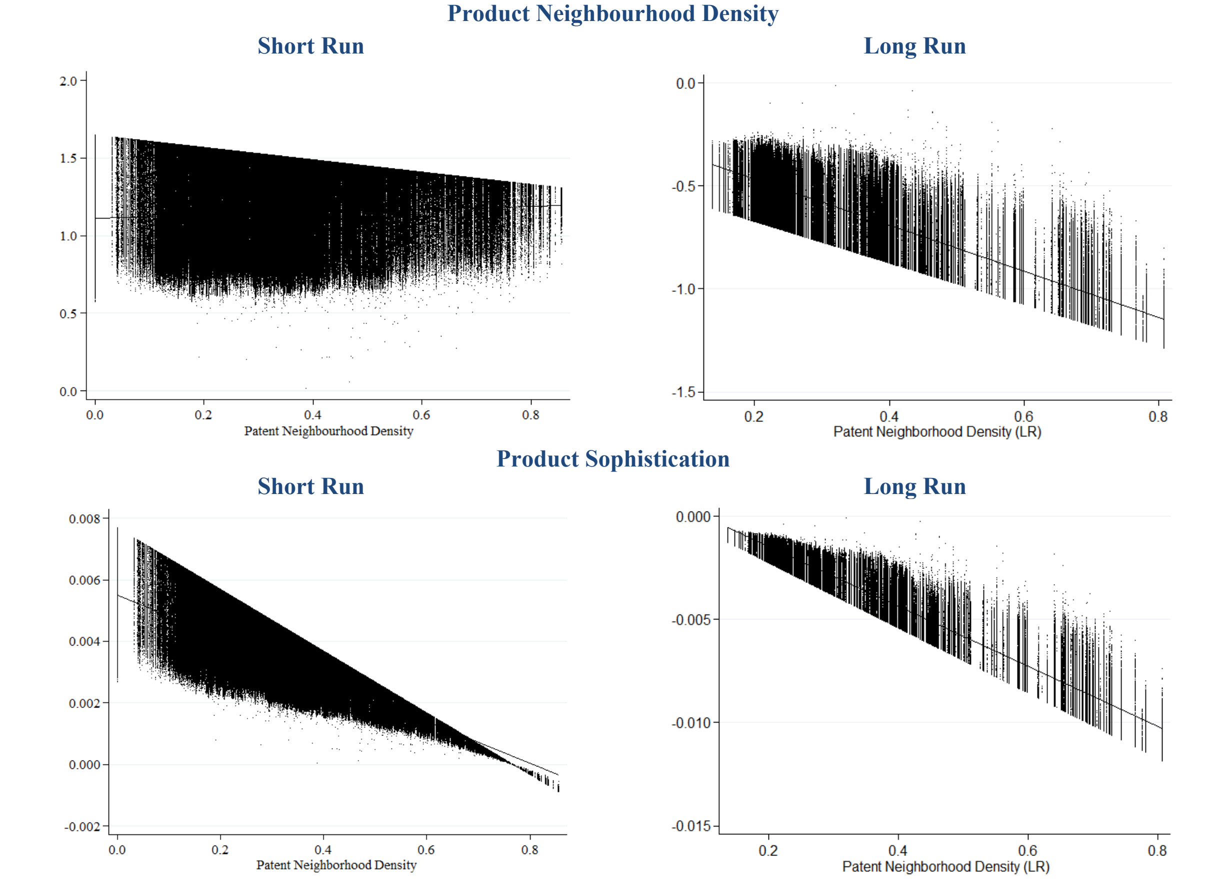
However, when including interaction terms with product neighbourhood density in the regressions, the impact of patent neighbourhood density turns significantly positive (see the sign of the partial effects of pat_dens and pat_dens_mean in columns (2) and (3) of Table 3.10). In product classes that are not related to the country's productive structure (i.e. for product classes with low product neighbourhood density) higher relatedness to the country's patenting activities (i.e. higher patent neighbourhood density) has a positive effect on specialising in the respective product. In other words, patenting activities help tapping new fields that are related to the patenting activities but unrelated to the existent industry structure. This holds for both the short (pat_dens) and the long run (pat_dens_mean).

When looking at the effect of product neighbourhood density on specialisation, for specialising in a product class it is less important that related productive structures are already existent when the product class is closely related to a country's patenting activities (see the overall positive effect but with downward slope in upper left panel in Figure 3.8[26]). Similar to education and skills, patenting activities reduce path dependency in productive structures. On the contrary, as already mentioned above, the relatedness in patenting activities reinforces sluggishness of productive structures in the long run. As already explained, the latter is induced by the negative

[26] The partial effect of product neighbourhood density on standardised RCA is always positive irrespective of the level of patent neighbourhood density. For all observations in the panel, the partial effects are above zero. However, the effect of product neighbourhood density is lower (but still positive) the higher the patent neighbourhood density which becomes observable when moving to the right in the panel.

long-run effect of product neighbourhood density[27] while the negative interaction term between product and patent neighbourhood density (see the downward slope in upper right panel in Figure 3.8) induces its reinforcement.

**Figure 3.8 The effect of product neighbourhood density and product sophistication on Standardised Revealed Comparative Advantage depending on patent neighbourhood density, sample of EU-28 countries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. OECD Regpat, BACI dataset (Gaulier and Zignago 2010)*

Using the pooled sample of EU Member States, patent neighbourhood density affects specialisation patterns with regard to the sophistication of the product portfolio negatively. In other words, the more closely related a product class to the country's innovation activities, the lower the positive short-run effect and the higher the negative long-run effect of product sophistication on specialisation (see lower panels in Figure 3.8). As explained above, the positive short-run effect is explained by the higher probability of EU Member States to specialise in more sophisticated products (in comparison to other non EU Member States). Their comparative advantage is mainly based on technological and less on cost advantages. The negative interaction term is therefore at first glance counterintuitive as one would expect that innovation activities improve the product portfolio. However, differentiating between different country groups depending on their stage of economic and technological development reveals that this negative interaction effect is dominated by countries in catching-up processes. For the most advanced EU Member States the interaction is positive (see lower panels in Figure 3.9). This result reflects the fact that countries at the technological frontier focus their patenting activities on average on more sophisticated technologies where the cumulativeness of knowledge plays an even more important role[28]. A higher relatedness to the country's patenting activities therefore also helps specialising in the more sophisticated related products. For catching-up countries, a higher relatedness to patenting activities implies that these

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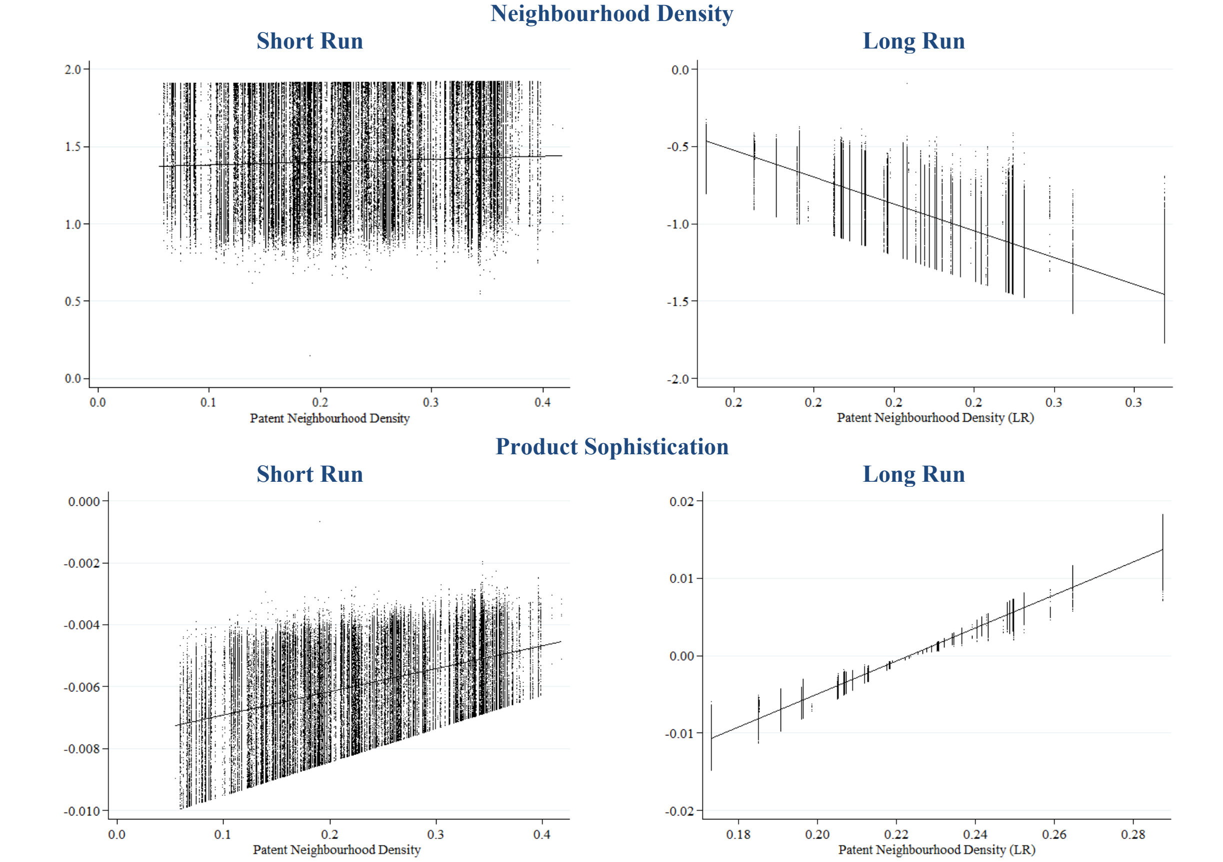
27 All observations in the upper right panel in Figure 3.8 are below the x-axis.

28 In 2014, the top fields of patent applications filed with the EPO were Medical technology, Electrical machinery, apparatus, energy and Digital communication. With a share of 12% of total applications Germany maintained its status as leading country within Europe. The technical fields with the highest growth rates were Biotechnology, IT methods for management and electrical machinery, apparatus and energy. (cf. European Patent Office 2015).

activities are related to less sophisticated technology fields. Therefore, higher relatedness to the country's patenting activities seems to slowdown the country's upgrading of the product portfolio while catching up. However, this result should not be interpreted as hint that patenting activities are deteriorating economic performance of less advanced countries since the analysis does not reveal whether countries are involved in high-end products within a product class or not. Assuming that patenting activities lead to new or improved products, catching-up countries might of course also benefit from their innovation activities climbing up the quality ladder (within the product classes the country is already specialised in) but not improving the product portfolio itself (i.e. structural change switching to more sophisticated product classes).

**Figure 3.9 The effect of product neighbourhood density and Product Sophistication on Standardised Revealed Comparative Advantage depending on patent neighbourhood density, sample of EU Member States with high direct and indirect R&D intensity**




*Note : Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation ; 'EU Member States with high direct and indirect R&D intensity' refers to the most advanced country group as defined Table 1.2.*
*Source: WIFO calculations. OECD Regpat, BACI dataset (Gaulier and Zignago 2010)*

As already described, the negative long-run effect of product sophistication (see soph_mean in Table 3.5) reflects the fact that it is more difficult to specialise in more complex products. For the long-run interaction effect between product sophistication and patent neighbourhood density on specialisation, the same pattern appears as for the short run effect. In the pooled sample, the results indicate that it is even more difficult to specialise in more complex products the closer related they are to the patent space (see lower right panel in Figure 3.8). Analogously to the short run, the effect in pooled sample of EU Member States is dominated by the less advanced countries. For the most advanced countries, the long-run interaction effect is positive indicating that they more easily specialise in more sophisticated products if their innovation activities are also related to these products (lower right panel in Figure 3.9). For products that are less related to the countries' patenting activities, the effect of product sophistication is even negative (shown in the leftmost position in the panel). This result fits the conjecture that the frontier countries' comparative advantage is based on both already being specialised in the more sophisticated products and by maintaining this advantage through deepening their knowledge base through innovation[29].

*Specialization patterns and knowledge inflows*

As described above, education and skills are important factors building up knowledge capabilities necessary to foster the improvement of a country's product portfolio as well as specialization patterns but they also allow gaining world market shares. However, in principal there also exist alternative options than domestic education in order to improve the knowledge base. The study therefore also analyses other sources of knowledge, in particular inflows from foreign countries via imports or foreign direct investments. The analyses – due to data constraints restricted to the sample of EU-28 countries only – show that the share of employment from foreign owned firms in total employment (manufacturing only) is positively correlated with world market shares both in the long run and the short run (see Table 3.11, column (1)). Foreign companies seem to support a country in gaining world market shares. The same holds for comparative advantage. Countries with higher shares of foreign owned companies tend to have higher RCA values. When investigating the share of employment of foreign owned firms in total employment within an industry, the long run effects are negative. Taken together these results hint that FDI positively affects the economy as a whole, which is in line with previous literature (see Zahra, Ireland and Hitt 2000, Buckley, Clegg and Wang 2007, or Sinha 2009) [30]. On the other hand, for the sectors themselves high shares of foreign owned firms seem to help gaining market shares and specializing in the respective sector only in the short run. In the long run higher shares of foreign owned firms tend to reduce comparative advantage (see Table 3.11, column (5)). This result might be explained by knowledge spillovers to other sectors but lack of spillovers within a sector as companies try to minimize knowledge outflows to direct competitors (for instance protecting their technologies via patents or trademarks)[31]. Furthermore, foreign owned firms are more likely than domestic firms to migrate to other countries when cost structures or other changes in the company's environment occur (e.g. change in infrastructure or tax system etc., see e.g. Görg and Strobl (2003) for UK, Alvarez and Görg (2009) for Chile or Ferragina, Pittiglio and Reganati (2014) for Italy)[32]. If these companies leave the country, they deteriorate the country's specialization in the respective sector (whereas the short run effect was positive) but the positive benefits and spillovers to other sectors might persist.

This pattern is also supported by results from regressions for different country groups. When comparing the long run effects of the share of foreign owned companies in the country on RCAs between the more advanced countries (country groups 1 & 2) and the rest, a significantly negative sign is found for the former and a significantly positive for the latter (see Table 3.13) (see Buckley, Clegg and Wang 2007). The spillovers from foreign owned firms to other firms in the country are lower in more advanced countries as they already built up the knowledge and capabilities. Therefore, the long run effects for this indicator are negative as well indicating that the risk of drifting firms might outperform the lower level of spillovers from inward FDI in the most advanced EU countries.

On the other hand, interaction effects between the share of foreign owned firms and product sophistication are significantly positive both on world market shares and RCAs[33] in the long run, turning the effect of product sophistication from a negative sign (in the case of small shares of foreign owned firms) into a positive one given that the share of foreign owned firms is high enough (graphs shown in appendix). While there is a potential risk that foreign owned firms are more likely to leave a host country again, they also seem to support the upgrading of the product portfolio in the long run. On the other hand, in the short run the results show the opposite sign (again reversing the sign of the effect) probably fitting the pattern that firms are more likely to set up production of less sophisticated products when entering a country they have not been settled before[34]. Afterwards the production of more sophisticated products and probably R&D facilities may follow.

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[29] For a discussion about product space and structural transformation see e.g. Hausmann and Klinger (2006), Hidalgo et al. (2007) or Cadot, Carrère, Strauss-Kahn, (2011).

[30] Sinha (2009) finds a positive effect of FDI on the host country's welfare in the case of appropriate licensing structures. In their paper Buckley, Clegg and Wang (2007) stress a positive impact of inward FDI on Chinese domestic industry. However, the effect crucially depends on the nationality of the investors and is particularly pronounced for low-tech host industries.

[31] This supports Girma, Greenaway, Wakelin (2001) who does not find aggregate evidence for intra-industry spillovers of FDI. However, Javorcik (2004) empirically shows that productivity spillovers take place through backward linkages.

[32] Further, Inui et al. (2009) shows that, in particular, vertically integrated foreign firms are more likely to exit because they are more sensitive to changes in costs of production.

[33] The result is not robust for explaining RCAs when including interaction effects for both neighbourhood density and product sophistication.

[34] Harzing (2002) points out that the dominant global strategic requirement is efficiency. Thus multinational companies integrate and rationalize their production in host countries to produce standardized and very cost-efficient products. In that case subsidiaries can be seen as pipeline for headquarters and as a result they do not react significantly to local market demands.

In the most advanced EU countries (see country groups 1&2 in Table 3.13) the share of foreign owned firms in total employment in manufacturing positively interacts with product sophistication in the short run when analysing RCA values. If foreign companies start investing in the most advanced countries they mainly focus on high end products as for less sophisticated products the wage levels are unfavourable in these countries. This rationale is in line with Sadik and Bolbol (2001) who state that FDI in developing countries is mostly efficiency-seeking, whereas in the developed countries the driving factor behind FDI is market seeking. This observed difference for advanced EU countries is in particular true when using an indicator measuring the share of FDI in manufacturing. If services are included one would expect a less clear cut pattern as the settling of headquarters might change the picture. Looking at manufacturing products only the results look quite reasonable.

**Table 3.11 Specialisation, product space and the share of foreign owned firms in total employment (manufacturing), product level regressions, sample of EU-28 countries, dependent variable = world market shares (wms)**

| | EU-28 countries QML Flogit Estimator | | | | EU-28 countries QML Flogit Estimator | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** | **APE** | **Sign** | **Sign** | **Sign** |
| **World market share, wms** | **(p-value)** | | | | **(p-value)** | | | |
| Lagged world market share, L.wms | 0.095 *** | +++ | +++ | +++ | 0.103 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| World market share time t=0, $wms_{t=0}$ | 0.020 *** | +++ | +++ | +++ | 0.018 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 0.135 *** | +++ | +++ | +++ | 0.120 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -0.002 | --- | 0 | --- | 0.011 *** | --- | --- | --- |
| | (0.332) | | | | (0.000) | | | |
| Product sophistication, soph | 0.000 | 0 | +++ | +++ | 0.000 ** | +++ | +++ | +++ |
| | (0.347) | | | | (0.010) | | | |
| Product sophistication (LR), soph_mean | 0.000 | - | --- | --- | -0.001 *** | --- | --- | --- |
| | (0.275) | | | | (0.000) | | | |
| Foreign owned companies (share in manufacturing) | 0.040 *** | +++ | +++ | +++ | | | | |
| | (0.000) | | | | | | | |
| Foreign owned companies (share in manufacturing, LR) | 0.907 *** | +++ | +++ | +++ | | | | |
| | (0.003) | | | | | | | |
| Interaction Neighb.density x For. owned comp. (manufacturing) | | --- | | --- | | | | |
| Interaction Neighb.density x For. owned comp. (manufacturing, LR) | | +++ | | +++ | | | | |
| Interaction Prod. Soph. x For. owned comp. (manufacturing) | | | --- | --- | | | | |
| Interaction Prod. Soph. x For. owned comp. (manufacturing, LR) | | | +++ | ++ | | | | |
| Foreign owned companies (share in NACE-2dig) | | | | | 0.005 *** | +++ | +++ | +++ |
| | | | | | (0.003) | | | |
| Foreign owned companies (share in NACE-2dig, LR) | | | | | -0.003 ** | --- | - | --- |
| | | | | | (0.038) | | | |
| Interaction Neighb.density x For. owned comp. (NACE-2dig) | | | | | | --- | | --- |
| Interaction Neighb.density x For. owned comp. (NACE-2dig, LR) | | | | | | +++ | | +++ |
| Interaction Prod. Soph. x For. owned comp. (NACE-2dig) | | | | | | | --- | --- |
| Interaction Prod. Soph. x For. owned comp. (NACE-2dig, LR) | | | | | | | +++ | +++ |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 666,900 | 666,900 | 666,900 | 666,900 | 545,532 | 545,532 | 545,532 | 545,532 |
| Pseudo $R^2$ | 0.784 | 0.785 | 0.784 | 0.785 | 0.801 | 0.802 | 0.801 | 0.802 |
| Deviance | 5260 | 5228 | 5251 | 5223 | 4038 | 4019 | 4033 | 4016 |
| Log Pseudolikelihood | -29570 | -29554 | -29566 | -29552 | -24867 | -24857 | -24865 | -24856 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note : APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively, : ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

In contrast, long run effects are negative for advanced countries. This result provides evidence for product life cycles issues. While foreign owned firms potentially bring along new knowledge when they set up a new subsidiary in a country (i.e. short run effect), they are less likely than domestic firms to move into new products. The domestic firms in frontier countries are on average more innovative than in other countries. In other words, once a production of a specific product (or group of products) is established, the product portfolio of the foreign owned firm is less flexible than for domestic, on average more advanced firms. Following product life cycle considerations, the product sophistication of these firms decreases relatively as other innovative products are continuously introduced. The less flexible foreign owned firms therefore tend to fall behind domestic firms. This effect is most severe in the frontier countries, as the foreign owned firms tend to help to improve the product portfolio in the short run (as explained above) but in the long run tend to decrease the average sophistication of the product portfolio. The long run interaction effects for the country groups 1&2 are therefore negative (see Table 3.13)[35].

[35] Cantwell (1989) stresses that knowledge-seeking FDI strongly depends on a country's education level, R&D intensity and institutional linkages between education and firms. Kuemmerle's (1999) results suggest that by establishing R&D facilities abroad firms in

**Table 3.12 Specialisation, product space and the share of foreign owned firms in total employment (manufacturing), product level regressions, sample of EU-28 countries, dependent variable = standardised revealed comparative advantage (srca)**

| | EU-28 countries | | | | EU-28 countries | | | |
|---|---|---|---|---|---|---|---|---|
| | QML Flogit Estimator | | | | QML Flogit Estimator | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** | **APE** | **Sign** | **Sign** | **Sign** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | | | | **(p-value)** | | | |
| Lagged standardised revealed comparative advantage L.srca | 0.536 *** | +++ | +++ | +++ | 0.559 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.115 *** | +++ | +++ | +++ | 0.119 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 1.923 *** | +++ | +++ | +++ | 1.819 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -1.403 *** | --- | --- | --- | -1.350 *** | --- | --- | --- |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication, soph | 0.001 * | +++ | +++ | +++ | 0.006 *** | +++ | +++ | +++ |
| | (0.072) | | | | (0.000) | | | |
| Product sophistication (LR), soph_mean | -0.001 ** | --- | --- | --- | -0.008 *** | --- | --- | --- |
| | (0.028) | | | | (0.000) | | | |
| Foreign owned companies (share in manufacturing) | 0.300 *** | +++ | +++ | +++ | | | | |
| | (0.000) | | | | | | | |
| Foreign owned companies (share in manufacturing, LR) | 13.119 *** | +++ | +++ | +++ | | | | |
| | (0.000) | | | | | | | |
| Interaction Neighb.density x For. owned comp. (manufacturing) | | --- | | --- | | | | |
| Interaction Neighb.density x For. owned comp. (manufacturing, LR) | | +++ | | +++ | | | | |
| Interaction Prod. Soph. x For. owned comp. (manufacturing) | | | --- | --- | | | | |
| Interaction Prod. Soph. x For. owned comp. (manufacturing, LR) | | | +++ | 0 | | | | |
| Foreign owned companies (share in NACE-2dig) | | | | | 0.021 ** | +++ | 0 | +++ |
| | | | | | (0.037) | | | |
| Foreign owned companies (share in NACE-2dig, LR) | | | | | -0.004 | --- | 0 | --- |
| | | | | | (0.683) | | | |
| Interaction Neighb.density x For. owned comp. (NACE-2dig) | | | | | | --- | | --- |
| Interaction Neighb.density x For. owned comp. (NACE-2dig, LR) | | | | | | +++ | | +++ |
| Interaction Prod. Soph. x For. owned comp. (NACE-2dig) | | | | | | | --- | --- |
| Interaction Prod. Soph. x For. owned comp. (NACE-2dig, LR) | | | | | | | +++ | +++ |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 666,900 | 666,900 | 666,900 | 666,900 | 545,532 | 545,532 | 545,532 | 545,532 |
| Pseudo $R^2$ | 0.830 | 0.831 | 0.830 | 0.831 | 0.833 | 0.833 | 0.833 | 0.833 |
| Deviance | 69854 | 69470 | 69828 | 69454 | 54873 | 54706 | 54850 | 54684 |
| Log Pseudolikelihood | -202155 | -201963 | -202142 | -201955 | -170527 | -170443 | -170516 | -170433 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively, : ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

A further empirical result also fits to this interpretation. A robust and significantly negative short-run interaction effect is observed between the share of foreign owned firms and product neighbourhood density again on both world market shares and RCA values for the pooled sample of EU-28 countries. In the long run, the sign reverses but the overall long run effect of neighbourhood density on RCA values remains strongly negative[36]. This result suggests that in the short run FDI reduces the barriers for entering new industries that are less close to a country's product space allowing to escape the existing industry structure more easily. From the point of view that foreign firms bring along new knowledge when establishing subsidiaries, the short run effects seem very plausible as these knowledge inflows can increase the knowledge base. However, in the long run foreign firms might concentrate their more sophisticated activities in those countries that fit their requirements best (i.e. via availability of capabilities etc.). Studies concentrating on the relationship between cluster development and inward FDI support these findings (see e.g. De Propris and Driffield 2006). Pre-existing domestic clusters attract foreign firms and result in both technology sourcing and foreign-to-domestic spillovers[37]. However, foreign firms are particularly attracted by industry clusters close to their own product portfolio, and thus an increase in FDI favours specialisation. In contrast to the pattern described above on the FDI share in total manufacturing, the same pattern is found for sectoral FDI shares for the more advanced but also the less advanced EU Member

technology-intensive industries can expand their technological capabilities. Because accessing new indigenous technology is more important than customizing existing technology for new products (see Florida 1997) it determines the encouragement in FDI.

36 When explaining world market shares the negative effect of neighbourhood density becomes positive with higher shares of foreign owned firms.

37 The phenomenon of `reverse spillover' effects is studied by Driffield and Love (2003). They emphasize that technology generated by the domestic sector spills over to foreign multinational enterprises. However, this effect is restricted to relatively research and development intensive sectors. Therefore, one would expect to find little positive impact of inward FDI in most advanced EU countries with a highly sophisticated product portfolio in particular.

States (see Table 3.13). This interpretation is also in line with the assumed pattern described above that firms set up less sophisticated activities first and more sophisticated may follow[38].

**Table 3.13 Specialisation, product space and the share of foreign owned firms in total employment (manufacturing), product level regressions for different country groups, dependent variable = standardised revealed comparative advantage (srca)**

| | Variable | | Interaction Term - Neighbourhood Density | | Interaction Term - Product Sophistication | |
|---|---|---|---|---|---|---|
| | Short Run | Long Run | Short Run | Long Run | Short Run | Long Run |
| Foreign owned companies (share in manufacturing) | | | | | | |
| Country Groups 1&2 | + | - | - | + | + | - |
| Country Group 3 | + | + | - | + | - | (+) |
| Country Group 4 | +/- | + | - | + | +/- | (+) |
| Country Group 5 | +/- | + | - | + | (-) | (+) |
| Foreign owned companies (share in NACE-2dig) | | | | | | |
| Country Groups 1&2 | (+) | (-) | - | + | 0 | (+) |
| Country Group 3 | + | (-) | - | + | - | (+) |
| Country Group 4 | (+) | (-) | - | + | 0 | (+) |
| Country Group 5 | +/- | +/- | - | + | - | + |
| Sophistication of imported capital goods | | | | | | |
| Country Groups 1&2 | + | + | - | + | + | +/- |
| Country Group 3 | + | + | 0 | + | - | + |
| Country Group 4 | - | + | + | - | (+) | - |
| Country Group 5 | + | + | - | - | - | + |
| Soph. of imported capital goods (parts and accesories thereof) | | | | | | |
| Country Groups 1&2 | + | + | + | + | + | +/- |
| Country Group 3 | (+) | + | - | + | - | + |
| Country Group 4 | + | + | - | +/- | (-) | - |
| Country Group 5 | + | + | (-) | + | - | + |

*Note: + ... robustly sign. positive coefficient in all tested equations, (+) ... positive but not always significant, - ... robustly sign. negative coefficient in all tested equations, (-) ... negative but not always significant, 0 ... neither sign. positive nor negative results, +/- contradicting significant results depending on the specified equation*
*Source: WIFO calculations*

When looking at knowledge inflows via imports, the results indicate that the average sophistication of capital goods and industry supply imports is negatively correlated[39] with comparative advantage and world market shares of a country. This holds for both the sample of EU-28 countries and the pooled sample (results not shown here). This result hints that countries importing more sophisticated capital goods and industry supplies are more likely to be catching up countries and hence export less. Moreover, the countries that import more sophisticated industry supply and capital goods tend to export less sophisticated products (see Marvasi 2013). Again, one might expect that this result is driven by the fact that catching up countries tend to import more of these goods. For EU countries the sophistication of these imports correlates negatively with specialising in more sophisticated exported goods. For the pooled sample including non-EU countries, the short run effect is positive. This indicates that importing more sophisticated production inputs helps improving the sophistication of its exports. However, if a country does not manage to substitute these imports in the long run, importing the sophisticated products might hamper the improvement of the country's product portfolio (see Navaretti and Tarr 2000 or Falvey, Foster and Greenaway 2004).

On the other hand, in the short run, more sophisticated capital goods and industry supply imports enforce gaining world market shares of products that are related to the country's product space. In the long run they also allow gaining world market shares of less related products. In particular, this might be true when intermediate product imports are used to produce and export more sophisticated intermediate products (see Marvasi 2013). Furthermore, these imports also reduce path dependency (both in the short run and the long run) allowing for specialisation in products that are less related to the country’s product space.

The results described above do not distinguish between imports of capital goods and industry supplies. When differentiating between industry supply and capital goods imports, long run effects on world market shares and RCA values are positive for more sophisticated capital goods imports (see Table 3.14 for the sample of EU-28).

[38] For the most advanced countries, the pattern might deviate from what is found for the pooled country sample. Foreign firms could also directly start with highly sophisticated activities (e.g. R&D) when entering highly developed countries in order to reap the benefits from high levels of capabilities or the innovative environment. For instance, Chung and Yeaple (2008) argue that an important explanation for firms investing abroad is not catching up or technologically diversifying, but is using similar R&D efforts of others to overcome fixed R&D cost hurdles. These R&D activities are more often found in more advanced countries.

[39] Sometimes the coefficients for the short run effects are significantly negative if interaction terms with product neighbourhood density are included. However, in these cases the interaction terms are highly significantly negative.

Long-run effects are even stronger for products that are more closely related to the product space (the long-run interaction effect with product neighbourhood density is significantly positive) while in the short run the opposite pattern is observed. These results indicate that importing more sophisticated capital goods might help to overcome specialisation patterns by tapping into new technology fields or industries in the short run more easily. On the contrary, it might even reinforce existing specialisation patterns if it is maintained over a long time period. However, in this case it is not clear whether this reinforcement is negative as the results also show that importing more sophisticated capital goods over a long time period might also help upgrading a country's product portfolio as well as gaining market shares in more sophisticated products. However, the results are less robust than for other indicators and depend on the definition of capital goods.

**Table 3.14 Specialisation, product space and the sophistication of capital goods imports, product level regressions, sample of EU-28 countries, dependent variable = standardised revealed comparative advantage (srca)**

| | EU-28 countries | | | | EU-28 countries | | | |
|---|---|---|---|---|---|---|---|---|
| | QML Flogit Estimator | | | | QML Flogit Estimator | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** | **APE** | **Sign** | **Sign** | **Sign** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | | | | **(p-value)** | | | |
| Lagged standardised revealed comparative advantage L.srca | 0.505 *** | +++ | +++ | +++ | 0.505 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.102 *** | +++ | +++ | +++ | 0.102 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 1.487 *** | +++ | +++ | +++ | 1.486 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -0.865 *** | --- | --- | --- | -0.865 *** | --- | --- | --- |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication, soph | 0.005 *** | +++ | +++ | +++ | 0.005 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication (LR), soph_mean | -0.003 *** | --- | --- | --- | -0.003 *** | --- | --- | -- |
| | (0.000) | | | | (0.000) | | | |
| Sophistication of imported capital goods | 0.033 *** | +++ | +++ | +++ | | | | |
| | (0.000) | | | | | | | |
| Sophistication of imported capital goods (LR) | 2.343 *** | +++ | +++ | +++ | | | | |
| | (0.000) | | | | | | | |
| Interaction Neighb.density x Soph imp. capital goods | | --- | | --- | | | | |
| Interaction Neighb.density x Soph imp. capital goods (LR) | | +++ | | +++ | | | | |
| Interaction Prod. Soph. x Soph imp. capital goods | | | --- | --- | | | | |
| Interaction Prod. Soph. x Soph imp. capital goods (LR) | | | +++ | +++ | | | | |
| Soph. of imported capital goods (parts and accesories thereof) | | | | | 0.025 *** | +++ | +++ | +++ |
| | | | | | (0.000) | | | |
| Soph. of imported capital goods (parts and accesories thereof, LR) | | | | | 2.792 *** | +++ | +++ | +++ |
| | | | | | (0.000) | | | |
| Interaction Neighb.density x Soph imp. capital goods (p&a) | | | | | | --- | | --- |
| Interaction Neighb.density x Soph imp. capital goods (p&a, LR) | | | | | | +++ | | +++ |
| Interaction Prod. Soph. x Soph imp. capital goods (p&a) | | | | | | | --- | --- |
| Interaction Prod. Soph. x Soph imp. capital goods (p&a, LR) | | | | | | | 0 | 0 |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 1,255,743 | 1255743 | 1255743 | 1255743 | 1,255,743 | 1255743 | 1255743 | 1255743 |
| Pseudo $R^2$ | 0.818 | 0.819 | 0.818 | 0.819 | 0.818 | 0.819 | 0.818 | 0.819 |
| Deviance | 141281 | 140608 | 141250 | 140600 | 141238 | 141192 | 141232 | 141187 |
| Log Pseudolikelihood | -373905 | -373568 | -373890 | -373564 | -373883 | -373861 | -373880 | -373858 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

One reason for the lower robustness of this indicator follows from the heterogeneity of the different country groups within the EU-28 countries. Repeating the regressions for the country groups already used above delivers noticeable differences in particular for the group of Greece, Italy, Portugal and Spain. In particular, the long run interaction effects of the sophistication of capital goods imports and product sophistication is negative[40] for this country group while it is positive for the other groups. While for the other country groups these imports help upgrading the product portfolio, for the mentioned southern EU Member States it is likely to reinforce structural traps. The results indicate that the more sophisticated capital goods imports substitute own production in these countries and therefore hamper a further upgrading of the product portfolio.

On the other hand, persistently importing more sophisticated industry supplies seems to affect world market shares and specialization patterns negatively. The coefficients of the long run effects are negative (results not reported). The regression results also indicate that importing more sophisticated industry supplies is correlated

[40] In addition the short run effect is also negative for this country group.

with a downgrading of the product portfolio in the long-run. The long-run interaction effects between the sophistication of exported products on the one hand and the sophistication of industry supply imports on the other hand are negative when analyzing either comparative advantage or world market shares. However, when looking at short run effects for the pooled sample (incl. non-EU countries) making use of highly sophisticated industry supply imports might also help improving the position of catching-up countries. However, as above the effect reverses in the long-run.

The analyses also include an alternative approach by measuring the degree of knowledge inflows via imports by calculating the share of imports from more advanced countries[41] in a country's total imports. The underlying idea is that exports of these countries contain on average a higher degree of embodied knowledge[42]. The results indicate that countries with high import shares from either EU-15 countries or innovation leaders achieve lower levels of world market shares on average. The coefficients for both long-run and short run effects are negative. However, importing more sophisticated products from these countries seems to help a country specializing in these products in the long run. Furthermore, importing products from these countries also mitigates the barriers to also specialize in the same products in the long run. In the short run the opposite pattern is observed for both product sophistication and relatedness. However, this result only holds for the sample of the EU-28. Repeating the regression for the pooled sample of all available countries the long run effects show the opposite sign. This pattern might result from the fact that only more advanced countries can benefit from more sophisticated imports and are able to absorb the embodied knowledge. If absorptive capacities are absent importing from more advanced countries might be more likely to substitute local production instead of letting knowledge spill over to the local economy.

## 3.3. SUMMARY

The empirical evidence found in chapter 3 exhibits high robustness of results. In particular the evidence found for the product space indicators used in the analyses is overall convincing although observing high persistency in the investigated industrial structures and comparative advantages. In the analysed group of countries, the Eastern European Member States underwent more dynamic structural change in export portfolios while other EU Member States show more mature industry structures. Furthermore, large countries on average export a larger number of products with comparative advantage than smaller ones.

Taking into account these country characteristics[43] the empirical evidence strongly suggests that specialising in new fields of technology (but also improving existing comparative advantages) depends on existing related capabilities. In the short run, high degrees of product relatedness support gaining world market shares and developing new or improving existing comparative advantage in closely related fields. On the contrary, high product relatedness also evokes sluggishness in economic structures limiting structural adjustments of the export basket of a country in the long run. While the most advanced countries are more heavily affected by potential sluggishness, the less developed a country the less predetermined its industry structure is. This result hints at a more settled industry structures in the former countries than in the latter.

Neighbourhood density measuring the relatedness of a product to the productive structures is the most important variable (except the lagged dependent variables) explaining variation in world market shares and specialisation patterns. For world market shares, a high neighbourhood density is favourable in both the short run and the long run.

Specialising in a product is more difficult for more sophisticated products. The higher the sophistication of products the lower the number of countries exporting a product as entering these markets requires higher levels of capabilities. However, comparing EU countries with other countries shows that the former are more likely to specialise in more sophisticated products as the majority of EU countries are advanced industrialised countries. For these countries it is more difficult to be competitive in products where lower levels of skills are required to enter world markets and less advanced countries can gain competitive advantage from lower wage levels. When redoing the analysis for different country groups within the EU the empirical evidence indicates that the closer countries are to the technological frontier the more competitive and specialised they are in more sophisticated products. With larger distance to the frontier it is less easy to specialise in these products.

The empirical results provide robust evidence that knowledge capabilities (i.e. education and skills) favour the development of new specialisations and a deepening of existing ones. Better educated countries are more

[41] „More advanced countries" are approximated by the group of innovation leaders (following the innovation union scoreboard) and alternatively by using the group of EU-15-countries (i.e. EU Member States before 2004).

[42] For a discussion of international knowledge flows and economic performance see e.g. Navaretti and Tarr (2000).

[43] These country characteristics are taken into account by controlling for country fixed effects.

specialised in niche markets, i.e. in products that are less commonly produced and exported. Knowledge capabilities overall allow gaining world market shares and developing new comparative advantages.

Furthermore, higher knowledge capabilities reduce the sluggishness in industry structures by reducing the importance of already existing related capabilities to develop new comparative advantage. The importance of skills is even more clear-cut when looking at world market shares. Higher levels of education help tapping into new industries and gaining world market shares that are less related to the country's product space. The empirical evidence also indicates that education and skills reduce difficulties to specialise in more sophisticated products in the long run. In the short run, the higher education and skills are the less distinctive is product sophistication for driving market shares.

Looking at the role of related knowledge generation capabilities reveals that close relatedness in patenting activities reinforces sluggishness in productive structures. This is in particular plausible as firms tend to focus their patenting activities to the fields of technology they are actively using in production. Nevertheless, specialising in products that are less related to existing productive structures is easier if these fields are more closely related to domestic patenting activities. Innovation activities therefore seem to build up competences required for improving comparative advantages in related fields. This is in particular relevant for countries at the technological frontier. These countries furthermore focus their patenting activities on average on more sophisticated technologies where the cumulativeness of knowledge plays an even more important role and a higher relatedness to the country's patenting activities therefore also helps specialising in the more sophisticated related products.

Knowledge and skills can also inflow into the country, for instance via foreign direct investments or via imports embodying related knowledge. The empirical analysis carried out in chapter 3 suggests that higher shares of FDI positively affect the economy as a whole. On the other hand, for the sectors themselves high shares of foreign owned firms within the sector seem to support gaining market shares and specializing in the respective sector only in the short run. In the long run higher shares of foreign owned firms tend to reduce comparative advantage. While knowledge spills over to other sectors domestic firms within the respective sector might face a lack of spillovers as companies try to minimize knowledge outflows to direct competitors. In the long run, foreign owned firms are more likely than domestic firms to migrate to other countries when cost structures or other changes in the company's environment occur. By leaving the country again, the foreign companies deteriorate the country's specialization in the respective sector but the positive knowledge spillovers to other sectors might persist.

However, while there is the potential risk that foreign owned firms are more likely to leave a country again, these firms seem to support the upgrading of the product portfolio in the long run. Higher shares of FDI are anyway less favourable for the average sophistication of the product portfolio in the short run. This result fits the so-called stage model of internationalisation that firms are more likely to set up production of less sophisticated products first when entering a country they have not been settled before. Afterwards the production of more sophisticated products and probably R&D facilities may follow.

Nevertheless, in the short run foreign firms support tapping new technology fields or industries that are less closely related to already existing productive structures. If bringing along knowledge otherwise not available in the host country, foreign firms might allow escaping from existing industry structures. In the long run high shares of FDI reinforce already existing specialisation since foreign firms concentrate their activities in those countries that fit their requirements best.

Considering differences in the stage of economic development shows that the most advanced countries benefit less from spillovers from foreign owned firms than catching up countries. The former group of countries rather built up the knowledge and capabilities itself already. These countries therefore face a negative impact of higher degrees of inward FDI on world market shares and specialization patters in the long run. On the contrary, FDI positively affects the sophistication of the product portfolio in the most advanced EU Member States in the short run. If foreign companies start investing in the most advanced countries they mainly focus on high end products as for less sophisticated products the wage levels are unfavourable in these countries. This is in particular true as the indicator measures the share of FDI in manufacturing. If including services one would expect a less clear cut pattern as the settling of headquarters might change the picture. Looking at manufacturing products only, the results look quite reasonable.

However, FDI negatively affects specialisation in more sophisticated products in the most advanced countries in the long run. This result provides evidence for product life cycles. While foreign owned firms potentially bring along new knowledge when they set up a new subsidiary in a country (i.e. short run effect), they are less likely than domestic firms (of the most advanced countries) to move into new products. In other words, once a production of a specific product (or group of products) is established, the product portfolio of the foreign owned firm is less flexible than for domestic firms. Following product life cycle considerations, the product sophistication of foreign owned firms decreases relatively as other innovative products are continuously introduced. The less flexible foreign owned firms therefore tend to fall behind domestic firms. This effect is most severe in the frontier countries, as the foreign owned firms tend to help to improve the product portfolio in the short run (as explained above) but in the long run tend to decrease the average sophistication of the product portfolio.

Finally, importing more sophisticated capital goods helps overcoming specialisation patterns (by tapping into new technology fields or industries in the short run more easily) but enforces these patterns if it is maintained over a long time period. However, it is not clear whether reinforcing specialization patterns is negative as the empirical evidence also shows that importing more sophisticated capital goods (the same holds for industry supplies) over a long time period also helps upgrading a country's product portfolio as well as gaining market shares in more sophisticated products. Within EU Member States, for the country group of Greece, Italy, Portugal and Spain the evidence hints at more sophisticated capital goods imports deteriorating the country's product portfolio and reinforcing structural traps. Capital goods imports seem to substitute domestic production here and therefore hamper a further upgrading of the product portfolio. For the remaining EU Member States, capital goods imports show positive stimulus for the sophistication of the countries' product portfolios.

Chapter 4.

# DIVERSIFICATION PATTERNS AT THE REGIONAL LEVEL AND THEIR RELATIONSHIP TO REGIONAL KNOWLEDGE CAPABILITIES

The aim of this chapter is to break down product space indicators obtained at the national level to the regional level and to examine the relationship between knowledge capabilities and (imputed) regional product sophistication and industrial specialisation econometrically. The first section of the chapter describes how this break down of the indicators to the regional NUTS 2 level has been carried out. Using this methodology regional indicators on product sophistication and relatedness, and industrial specialisation patterns are obtained. These indicators are analysed jointly with regional indicators on knowledge capabilities. The regional industrial specialisation patterns are identified by calculating regional RCAs based on value added and employment data taken from a regional industry structure matrix. This matrix is furthermore used for the imputation of national indicators to regions.

Similarly to the empirical analysis carried out in chapter 3, section 4.2 presents results for the econometric analysis of the effects of existing regional specialisation patterns in production and of various indicators of knowledge capabilities on developing new specialisations at the regional level. The analysis and the hypotheses are essentially identical to those presented in chapter 3, but the level of analysis will be the regional one. Moreover, due to limitations in regional data the analysis cannot be carried out at the product level and therefore has to focus on the more aggregated NACE Rev. 2 4-digit industry level.

Using the results, the chapter will finally take a closer look at a few regions that the analysis identified as showing particularly interesting patterns (presented in the appendix). The focus of these case studies is to present the statistical material for selected EU regions in detail and discuss it on the background of additional material available from existing studies such as the Regional Innovation Scoreboard[44], the Regional Innovation Monitor[45], as well as from other pertinent case studies and material.

## 4.1. PREPARING THE DATASET FOR NUTS2 REGIONS

### 4.1.1. Calculating a regional industry structure matrix

One of the main issues to solve in order to analyse specialisation patters at the regional level was industry level data availability for NUTS2 regions. Chapters 4 and 5 focus on the analysis of patterns concerning product space and industry structure at the regional level. The main aim of chapter 4 is breaking down the analysis from the country level (chapter 3) to the regional level investigating whether the patterns observed at the country level are also reflected at the regional level. The main issue here is that representative trade data as they have been used in chapter 3 for the country level analysis are not available for regions and therefore had to be estimated.

Using Amadeus firm-level data provided by Bureau van Dijk allows allocating firms to NACE Rev.2 4-digit sectors. Amadeus contains comprehensive information on around 21 million companies for the EU-28 and a few other countries. The database also includes information on the firms' address (incl. postal codes, city, etc.) and therefore provides the precondition for assigning these companies to regions. However, the main issue to solve using the Amadeus database is its lack in representativity. In particular, the coverage of firms in Amadeus is biased towards larger firms while small firms are strongly underrepresented. Which companies are covered does not depend on statistical considerations with respect to representativeness but on data availability.

In order to come up with a reliable estimate for employment or value added in NUTS2 regions the following issues had to be solved:

- First, the information on the location of each firm (address, postal code or city) had to be assigned to a NUTS2 region.
- Second, missing values in the data set (e.g. if information on a firm's employment or value added is not available for some years) had to be imputed in order to minimise potential bias due to lack of information.

[44] http://ec.europa.eu/enterprise/policies/innovation/policy/regional-innovation/
[45] http://ec.europa.eu/enterprise/policies/innovation/policy/regional-innovation/monitor/report/innovation

- Third, based on the first two steps regional aggregates have been calculated for NACE 4-digit industries in NUTS2 regions based on the filled up Amadeus database.
- Finally, the aggregates based on non-representative Amadeus data on NUTS2-NACE 4-digits level are adjusted with the official Structural Business Statistics available at Eurostat either at the NUTS2-NACE 2-digit level or at the NUTS0-NACE 4-digits level.

*Step 1: Assigning Amadeus firm level data to NUTS2 regions.*

This step aims at providing a concordance list linking Bureau van Dijk (BvD) identification numbers from Amadeus to NUTS2 regions. In a first step a list of Amadeus firms is complied including all relevant geographical information. From the geographical information the data imputation mainly relied on the information on postal codes and cities, whereby postal codes seem to be more reliable.

The assignment of the companies to NUTS2 regions made use of concordance lists from Eurostat containing postcodes and corresponding NUTS2 Codes[46]. These lists were available only for 16 EU countries (AT, BE, BG, CZ, EE, DE, DK, HR, HU, IT, LT, LV, MT, PT, RO, SK), whereas some of them were irrelevant as for some countries the NUTS0 level (country) equals the NUTS2 level. In other words, Estonia (EE), Lithuania (LT), Latvia (LV) and Malta (MT), but also Cyprus (CY) and Luxembourg (LU) only have one NUTS2-level (i.e. EE00). The postal codes NUTS concordance for UK has been taken from the official ONS website[47].

For the remaining EU-28 countries (i.e. EL, ES, FI, FR, IE, NL, PL, SE and SI) a concordance list had to be generated. Therefore, the postal codes and cities taken from Amadeus were geocoded (i.e. assigned coordinates to each of the postal codes and cities) using the open source software program QGIS. In order to be able to identify and correct erroneously assigned NUTS2 regions to postal codes or cities, different combinations of country code, postal code and city were used and their results contrasted. The resulting assignments were furthermore crosschecked with Regpat, the OECD's regional patent database where NUTS2 assignments and address information of patent inventors and applicants are available. Furthermore, using the 'Clear and Simply' database available online allowed another cross-check. This database also includes geocoded postal codes and cities. However, the database is not fully reliable and therefore was used as a further source for crosschecking the address-NUTS2 assignments only.

The resulting list has been completed using manually extractions from Eurostat's webportal WebILSE[48]. Manual adjustments had to be made whenever either the official concordance tables from Eurostat were not complete or the geocoding delivered contradicting results. Furthermore, typing errors in the Amadeus data (e.g. wrong postcodes or cities) had to be adapted and the missing NUTS2 codes filled up with the help of WebILSE.

Finally, manually adjusted assignments due to revisions in the NUTS classification system have been carried out whereby the final list of regions follows the 2010 NUTS revision. These changes again have been crosschecked with Eurostat's webportal WebILSE.

*Step 2: Impute missing values in Amadeus*

Starting point for imputing missing values in Amadeus was Eurostat's Structural Business Statistics database on the country-NACE 4-digits level. Missing values in the official dataset have been filled up via inter- and extrapolations. This dataset was merged with the Amadeus firm level database (incl. employment, value added, founding year, and the NUTS2 assignment). Due to data availability the sample was restricted to mining and quarrying (NACE (Rev. 2) B) and manufacturing (NACE (Rev. 2) C). Employment and value added have then been imputed in the Amadeus firm level data via inter- or extrapolation. If no data were available for a firm the values have been estimated using sector averages to impute them.

*Step 3: Calculating regional aggregates for NACE 4-digit industries in NUTS2 regions*

Based on the steps described above sectoral aggregates for NUTS2 regions were calculated using the imputed Amadeus firm level databases by summing up employment and value added within NACE 4-digits industries in NUTS2 regions. However, as explained above these aggregates are not representative as in general neither all companies are covered nor the covered companies represent a representative sample of all companies.

[46] http://ec.europa.eu/eurostat/web/nuts/correspondence-tables/postcodes-and-nuts
[47] https://geoportal.statistics.gov.uk/geoportal/catalog/main/home.page
[48] http://epp.eurostat.ec.europa.eu/WebILSE/localitySearch.do

*Step 4: Adjusting regional aggregates to official statistics*

Using RAS techniques developed for Input-Output analyses the regional NACE 4-digits aggregates have been contrasted with official SBS data. RAS calculates row (in this case the sum of a NACE 4-digits sector over regions within a country) and column sums (i.e. the sum of NACE 4-digits sectors within a NACE 2-digits sector in a NUTS2 region) of a matrix and compares them with the correct counterparts taken from official statistics (i.e. SBS statistics). Using an iterative procedure adjusting the row and column sums to the official statistics the procedure allows calculating a refined matrix were the values within the matrix are consistent with the official statistics. Finally, employment and value added shares a NACE 4digits industry of a region has been calculated within a country (or within all EU-28 countries).

However, inconsistencies occur whenever a firm is assigned to a NACE 4-digits industry in Amadeus but according to the official statistics there should not be a firm. The same holds for the other way round, i.e. if the official statistics claim that firms are active within an industry in a country but any firms in Amadeus are assigned to the respective industry in the country. In these cases the RAS approach does not converge and therefore the regional aggregates for industries do not fit to the official target values in some cases. However, for all NUTS2-NACE-4digits combinations only a very small share did not converge. For these cases the data have been crosschecked and manually corrected, for instance by dropping firms included in the Amadeus database.

In order to check the quality of the results the data have been compared with official employment statistics available for Austria. Differences from the official employment statistics for Austria might be explained by differences in the data collection. For instance, employees might be assigned to regions based on the place of residence of the employees or based on the place of work. Furthermore, Amadeus does not distinguish between establishments within an enterprise and only contains employees but does not cover self-employment. While the former is in particular relevant for multi-plant firms that might be located in different NUTS2 regions, the latter is in particular relevant for industries where small firms dominate. Another inconsistency between the data and official statistics might occur due to differences in counting employees (headcounts vs. number of employment relationships) or due to different reference days that cannot take into account seasonal fluctuations. All in all, the assessment of the data quality suggested that the reliability is high enough for empirical analyses. However, the dataset of course has a series of caveats that have to be taken into account in the analyses.

**Table 4.1 Summary statistics – Specialisation patterns in NUTS2 regions based on Employment or Value Added, NACE Rev. 2 4-digit industries**

| | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Standardised RCA (srca) | | | | | |
| Employment | 330750 | 0.25 | 0.29 | 0.00 | 1.00 |
| Value added | 330750 | 0.24 | 0.29 | 0.00 | 1.00 |
| EU Industry Shares (is) | | | | | |
| Employment | 330750 | 0.00 | 0.01 | 0.00 | 0.96 |
| Value Added | 330750 | 0.00 | 0.01 | 0.00 | 0.99 |

*Source: WIFO calculations. Bureau van Dijk (Amadeus), Eurostat (Structural Business Statistics)*

Table 4.1 summarises the resulting specialisation indicators (RCA values and EU industry shares) used in the analyses of chapter 4. The table shows very small differences between the data basis (employment or value added) used to calculate the indicators. The average standardised RCA value for the 245 NACE Rev. 2 4-digit industries is about 0.25. For EU industry shares (i.e. the share of a NUTS2 region in a NACE Rev. 2 4-digit industry within the EU-28) the average is 0.0037 for both versions.

### 4.1.2. Regional product sophistication and neighbourhood density of products

The indicators used to describe the sophistication of products and their relatedness (i.e. neighbourhood density) at the regional level are calculated following the same approach as for the country level. Details on their calculation on the product level are described in section 2.2.2. However, due to data constraints at the NUTS2 level the indicators have to be aggregated at the sectoral level (NACE Rev.2 4-digits) for this chapter.

In the case of product sophistication, the information on exports by product (i.e. the share of exports of a product in total exports) at the country level has been used to calculate average product sophistication for NACE Rev. 2 4-digit industries. Since no information is available which regions within a country produce which products within a 4-digit industry, the aggregation is based on the assumption that the product sophistication at the 4-digit industry level does not differ across regions within a country.

The neighbourhood density for NACE 4-digit industries for NUTS2 regions is calculated by first calculating the proximity matrix (as defined in formula (F4) in Box 2.2 for products) for NACE 4-digit industries. For products, the proximity measures the pairwise conditional probability of a country exporting one good given that it exports another. The proximity matrix therefore contains for each pair of different products a measure of how closely related these products are. They higher the number of countries exporting both products with revealed comparative advantage (i.e. RCA > 1), the higher the probability that these products are closely related to each other. Knowing the relatedness of products it is possible to calculate the proximity of NACE 4-digit industries by averaging the proximity of all products in the first sector to all products in the second sector resulting in a proximity matrix as in (F4) but now for NACE 4-digit industries instead of HS6-digit product groups. The proximity matrix of industry, which does not vary across countries by definition, is then used to calculate the neighbourhood density for NACE 4-digit industries for each NUTS2 region following formula (F5). Regional RCA values for NACE 4-digit industries required for calculating the neighbourhood density for NUTS2 regions are calculated from the regional industry structure matrix described in section 4.1.1. In the analyses, different alternatives of the regional industry structure matrix are used (based on employment and/or value added). However, due to lower reliability of value added data in the Amadeus firm-level database, the indicators based on value added only are skipped.

**Table 4.2 Summary statistics – Average product sophistication and neighbourhood density in NUTS2 regions, NACE Rev. 2 4-digit industries**

| | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Neighbourhood density (avg. VA & Empl.) | 281220 | 0.24 | 0.07 | 0.01 | 0.48 |
| Neighbourhood density (Empl.) | 281220 | 0.25 | 0.06 | 0.04 | 0.48 |
| Product Sophistication | 299422 | -0.01 | 0.72 | -3.12 | 1.87 |

*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010). Bureau van Dijk (Amadeus), Eurostat (Structural Business Statistics)*

However, the results of the empirical analyses presented in this chapter do not strongly differ across alternative approaches calculating the indicators. The differences are also hardly observable when looking at summary statistics for the main variables of interest. Table 4.2 summarises the indicators on product sophistication and neighbourhood density for NACE Rev. 2 4-digit industries in NUTS2 regions. While product sophistication at the HS6-digit product level varies between -4.57 and +3.37 (compare Table 2.2), average product sophistication at the NACE 4-digit industry level varies between -3.12 and 1.87. The extreme values are averaged out at the industry level. The same holds for neighbourhood density for the maxima. At the product level neighbourhood density varies on the unit interval. At the industry level the maximum is close to 0.5. The lower maximum for neighbourhood density is very reasonable, as expecting the most similar products being assigned to the same industries. The relatedness between more aggregated industries is therefore lower then within these industries.

### 4.1.3. Regional indicators on knowledge, education and skills

In principle, the indicators used in chapter 4 to measure education and skills at the regional level are the same as in chapter 3. However, due to lack in data availability at the regional level, the set of indicators is smaller. Table 4.3 summarises the education and skills variables used in chapter 4. Figure A.9 in appendix contrasts the performance of NUTS2 regions in selected indicators graphically. All in all, the indicators are of course correlated but there also exist some differences depending on their definition.

**Table 4.3 Summary statistics – Education and skills in NUTS2 regions.**

| | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Tertiary Attainment | 1330 | 25.49 | 8.70 | 6.80 | 63.00 |
| Persons with tertiary education OR employment in science/tech (% of act. Pop.) | 1350 | 37.39 | 8.96 | 12.80 | 72.30 |
| Persons with tertiary education AND employment in science/tech (% of act. Pop.) | 1340 | 16.75 | 5.04 | 5.50 | 40.70 |
| Persons with tertiary education (% of act. Pop.) | 1350 | 26.50 | 8.46 | 7.50 | 65.20 |
| Persons employment in science/tech (% of act. Pop.) | 1345 | 27.68 | 7.21 | 10.50 | 53.10 |
| Persons with tertiary education OR employment in science/tech (% of total empl.) | 2540 | 24.54 | 13.29 | 1.50 | 96.30 |
| Persons with tertiary education AND employment in science/tech (% of total empl.) | 1955 | 8.79 | 6.15 | 0.60 | 46.90 |
| Persons with tertiary education (% of total empl.) | 2500 | 17.89 | 11.20 | 0.90 | 74.30 |
| Persons employment in science/tech (% of total empl.) | 2150 | 16.15 | 10.53 | 0.70 | 66.40 |

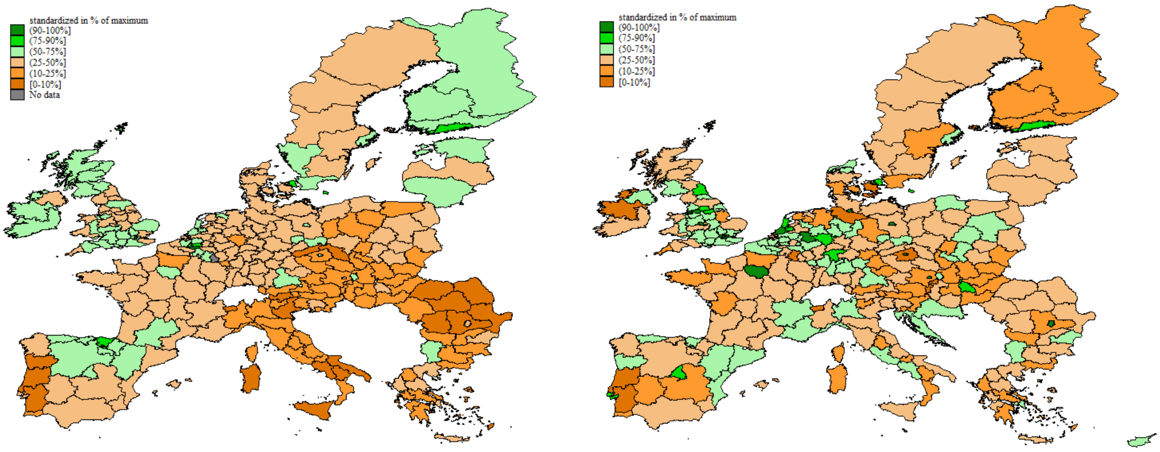
*Source: Eurostat*

In comparison to the national level, the distribution of education and skills is much more diverse at the regional level (compare left panel in Figure 4.1). While some differences occurring at the country level are also reflected at the regional level, the heterogeneity within countries is also significant. For instance, Finland is on average well performing in the share of population with tertiary attainment in all regions, but the highest shares are concentrated in the capital region in the south. The largest differences within a country are found in Spain, where the southern regions have much lower shares in tertiary attainment than the northern regions and in particular the Basque region.

**Figure 4.1 Education and population density. Controlling for regional characteristics**

**Share of population aged 25-64 with tertiary educational attainment (2012)**

**Share of households in densely populated areas (2010)**

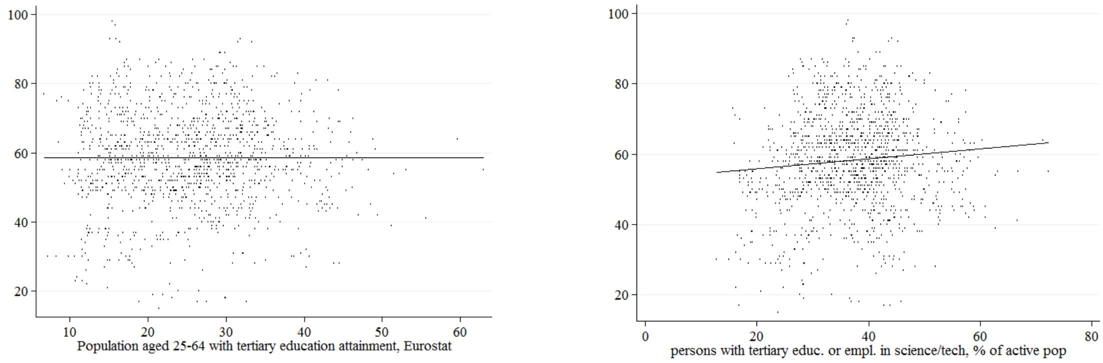



*Source: Eurostat*

The share of population with tertiary education (see left panel of Figure 4.1) is significantly correlated with the share of households located in densely populated areas (right panel). The correlation coefficient is about 0.429 in the sample of NUTS2 regions. The same holds for the other education and skills indicators used in the analyses of chapter 4 but for some of the variables the correlation coefficient is a bit lower. Furthermore, a capital region effect is observed, i.e. those regions where a country's capital is located have comparably higher shares of people with tertiary education and of persons working in science and technology. On the other hand, a significantly negative correlation appears between skill indicators and specialisation if the former are mainly based on the share of tertiary attainment. Overall, the observed patterns indicate that it is important to control for regional characteristics when analysing the effect of education on specialisation patterns.

**Figure 4.2 The relationship between education and skills (selected indicators) and the number of industries with RCA ≥ 1, NUTS2 regions**

**Share of population aged 25-64 with tertiary educational attainment** | **Share of persons with tertiary education or employed in science/tech, % of active population**




*Source: WIFO calculations. Eurostat, Bureau van Dijk (Amadeus)*

Figure 4.2 plots the number of NACE Rev. 2 4-digit industries with revealed comparative advantages within NUTS2 regions against two selected indicators for education and skills. The left panel shows that there is no obvious relationship between the share of the population with tertiary educational attainment in a NUTS2 region and the number of industries with RCA ≥ 1. The right panel hints at a positive relationship between the number of industries with RCA ≥ 1 and human resources in science and technology. The two figures shall illustrate that looking at tertiary education shows no link to specialisation at the NUTS2 level but taking into account also employment in science and technology a positive correlation is observed. This pattern is also confirmed by other indicators used (not presented here).

**Table 4.4 Summary Statistics – Knowledge generation**

| | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Patent neighbourhood density | 31165 | 0.25 | 0.15 | 0.00 | 0.80 |

*Source: OECD Regpat*

Analogously to patent neighbourhood density at the country level in chapter 3, the same indicator is used to approximate the relatedness of patenting activities within NACE 2-digit industries to the region's overall patenting activities. The calculation of the indicator follows the same definition as described in section 3.1 but now assigns the patents to NUTS2 regions using the address information of the applicants taken from OECD's Regpat database. Table 4.4 summarises the indicator for 23 NACE-2digit industries in 271 NUTS2 regions for the timeframe 2008-2012. Compared to the country level (0.35), the relatedness of patenting activities is on average lower for NUTS2 regions (0.25) indicating that patenting activities are less concentrated at the regional level. This effect is mainly driven by the on average lower numbers of patent applications within NUTS2 regions.

## 4.2. The relationship between specialisation, product sophistication and Knowledge Capabilities at the regional level

The hypotheses formulated for Eq. 2 (see chapter 3, Box 3.1) can be analogously adapted to the regional level. The hypotheses slightly change to:

**Box 4.1 Hypotheses tested in chapter 4**

Hypothesis 1: The development of new comparative advantages in a region is positively related to the relatedness of an industry to existing productive capabilities.

Hypothesis 2: The development of new comparative advantages in a region is decreasing with the level of sophistication of products.

Hypothesis 3: Knowledge capabilities increase the likelihood to develop new comparative advantages in a region.

Hypothesis 4: Knowledge capabilities allow escaping from existing specialisation patterns.

Hypothesis 5: Knowledge capabilities facilitate the upgrading of the industry portfolio.

### 4.2.1. Estimation design

The econometric analysis of the effects of regional specialisation patterns in production and of various indicators of knowledge capabilities on developing new specialisations at the regional level follows a similar approach as in chapter 3 for the country level. The analysis and the hypotheses are essentially identical to those developed in relation to Eq. 2 (see chapter 3). However, the level of analysis will be the regional industry level[49]. Only those knowledge capability indicators will be used that are available at the regional level. Eq. 2 thus changes to:

Eq. 3:
$$\mathrm{E}[\mathrm{SPEC}_{r,s,t}|x_{r,s,t}] = \mathrm{G}(\alpha_{r,s,t} + \beta_0 \mathrm{SPEC}_{r,s,t-1} + \beta_1 \mathrm{DENS}_{r,s,t} + \beta_2 \mathrm{CAP}_{r,t} + \beta_3[\mathrm{DENS}_{r,s,t} \times \mathrm{CAP}_{r,t}] + \beta_4 \mathrm{SOPH}_{r,s,t} + \beta_5[\mathrm{SOPH}_{r,s,t} \times \mathrm{CAP}_{r,t}] + \sum_t \lambda_t d_t + \sum_r \lambda_c d_c + \epsilon_{r,s,t}),$$

The indices now run over regions r and sectors s, and $\sum_c \lambda_c d_c$ are country dummies capturing unobserved variation at the country level. Due to econometric issues[50] it is not possible to include regional dummies in the regressions to capture regional fixed effects. If including the dummies the fractional logit model does not converge affecting the validity of results. The regressions therefore have to stick to country dummies. Furthermore, although the estimated equation at the NUTS2 level is similar to the country level, differences between the regional and the national level have to be considered. In particular, it has to be taken into account that regions can be much more heterogeneous than countries. For instance, if comparing rural regions without large urban centres with highly urbanised capital regions, both industry structure and skill levels probably strongly differ. Although similar differences might exist for different countries, for instance when comparing highly industrialised countries on the one hand and catching up countries on the other hand, these differences might be expected to be much more severe for different NUTS2 regions. The regressions therefore also include control variables for the size of the region (approximated by total employment in industry), the degree of urbanisation (i.e. the share of households in densely populated areas) and whether the country's capital is located in the region.

Concerning the dependent variables, from the theoretical point of view, considering differences in productivity levels would be preferable when empirically investigating specialisation indicators. However, the results observed are very similar independently of whether using RCAs or industry shares based on employment only or if also taking into account value added data (compare Table 4.1 for summary statistics of the dependent variables tested). Due to the higher reliability of the employment variables in the Amadeus database the remaining section focuses on presenting results using dependent variables based on employment as indicator for specialisation.

A main difference from the analysis carried out in chapter 3 is the alternative dependent variable approximating market shares. While data availability allows using world market shares for products at the country level (i.e. product level trade data are available for all countries), similar data are not available for regions. While industry share of NUTS2 regions within the EU (as described in section 4.1.1) can be estimated no reliable information to

[49] This chapter uses "at the regional level" in order to contrast the findings with those presented in chapter 3 (country level).Since the unit of observation in chapter 4 is the NACE Rev. 2 t-digit industry level, the analyses should not be mixed up with macroeconomic regressions for aggregated data at the regional level.

[50] No convergence in the maximum likelihood regressions has been achieved in the regressions if regional dummies are included.

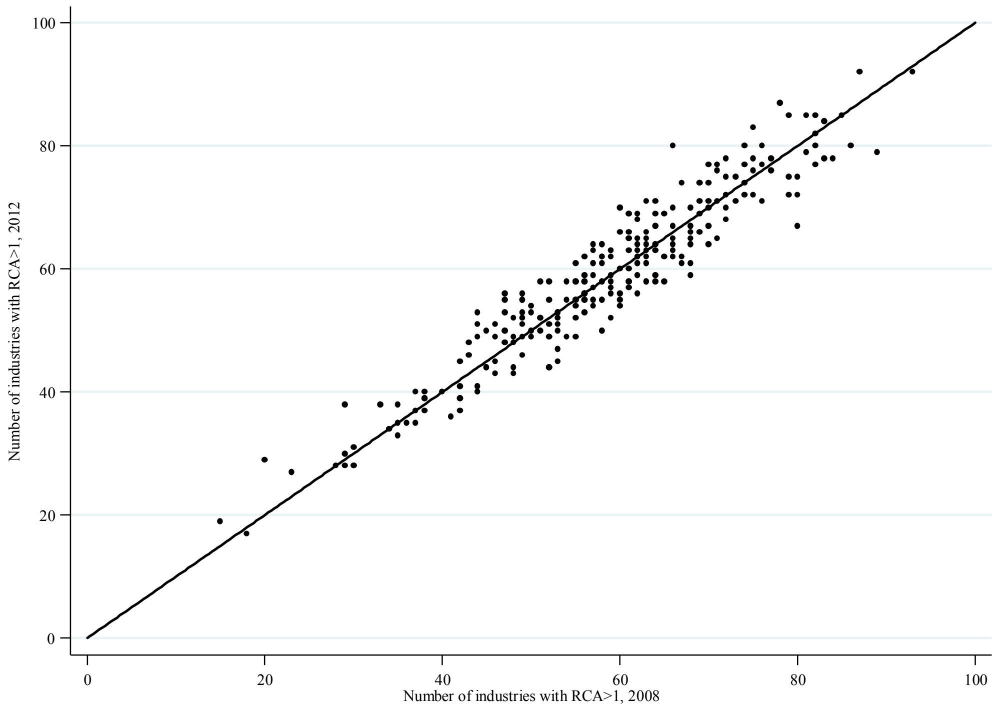
estimate the respective world market shares accurately is available. Since the EU's world market shares (over all Member States) differ across industries the interpretation of regional industry shares would be different from that of world market shares in chapter 3. This issue is however irrelevant for RCA values as the differences in EU's world market shares across industries are cancelled out by the denominator in the RCA formula. The analysis at regional level has therefore to be restricted to the share of a NUTS2 region within an EU industry and the presentation of results in section 4.2.2 focuses on the regressions explaining standardized RCA values (which are overall comparable with chapter 3).

### 4.2.2. Empirical Results

*Regional specialization patterns and the product space*

Figure 4.3 plots the number of industries in which a region had an RCA ≥ 1 in 2012 against the number of industries with RCA ≥ 1 in 2008. As has been shown in Figure 3.4 for countries, this figure illustrates a high level of persistency in comparative advantage across regions over time. The pattern is very similar when comparing the regional and the national level although the two figures are not directly comparable. Figure 3.4 covers a longer time frame where higher fluctuations might be expected. On the contrary, the higher heterogeneity at the regional level might also result in a less clear-cut relationship. Anyway, both effects are too small to change the picture.

**Figure 4.3 Persistency in the diversification of NUTS2-regions' industry portfolio**




*Source: WIFO calculations. Bureau van Dijk (Amadeus)*

In line with the results at the country level, a highly significantly positive effect of the lagged dependent variable is found when explaining RCAs and also EU industry shares at the NUTS2 level. This result indicates that NUTS2 regions strongly tend to maintain their comparative advantage in the following period if they had a comparative advantage in the previous one. The average partial effects explaining standardised RCAs are even higher than for the country level (see Table 4.5). The higher persistency found at the regional level is partially explained by the differences in the dependent variables used in chapters 2 and 4. Employment shares (used for calculating regional RCAs in chapter 4) are even stickier than export success (country level RCAs in chapter 3). This first result strongly confirms the persistency pattern already described in chapter 3 although the observed time frame for the analysis at the regional level is strongly prone to characteristics of the economic crisis. However, as the results are very similar to the longer time period covered in chapter 3 the economic crisis does not seem to have affected specialisation patterns heavily.

When looking at the regional control variables, robust patterns are observed. Larger NUTS2 regions (measured in terms of total employment in industry) have on average higher shares of RCA values in the long run. The short run coefficients are robustly negative but their partial effects are dominated by the positive long-run effect. When controlling for the share of households located in densely populated areas in total households a significantly positive relationship with RCA is found. However, the sign and significance of the coefficients of interest seem to remain unchanged independently of whether including the controls or not.

**Table 4.5 Specialisation, product space and knowledge capabilities, industry level regressions, NUTS2 regions, dependent variable = Standardised revealed comparative advantage (SRCA)**

| | | NUTS2 regions | | |
|---|---|---|---|---|
| | | QML Flogit Estimator | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | | | |
| Lagged standardised revealed comparative advantage L.srca | 0.589 *** (0.000) | +++ | +++ | +++ |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.087 *** (0.000) | +++ | +++ | +++ |
| Neighbourhood density, dens | 0.104 *** (0.000) | +++ | +++ | +++ |
| Neighbourhood density (LR), dens_mean | -0.007 (0.719) | --- | 0 | --- |
| Product sophistication, soph | -0.001 (0.467) | 0 | 0 | 0 |
| Product sophistication (LR), soph_mean | 0.005 *** (0.001) | +++ | 0 | 0 |
| Tertiary Educational Attainment, tert | 0.000 (0.568) | +++ | 0 | +++ |
| Tertiary Educational Attainment (LR), tert_mean | 0.000 (0.643) | --- | 0 | --- |
| Interaction Neighb.density x Tertiary Educational Attainment | | --- | | --- |
| Interaction Neighb.density x Tertiary Educational Attainment (LR) | | +++ | | +++ |
| Interaction Prod. Soph. x Tertiary Educational Attainment | | | 0 | 0 |
| Interaction Prod. Soph. x Tertiary Educational Attainment (LR) | | | 0 | 0 |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |
| Regional Control Variables | YES | YES | YES | YES |
| Number of observations | 212,719 | 212,719 | 212,719 | 212,719 |
| Pseudo $R^2$ | 0.938 | 0.938 | 0.938 | 0.938 |
| Deviance | 11493 | 11493 | 11490 | 11490 |
| Log Pseudolikelihood | -50695 | -50695 | -50693 | -50693 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively: ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

**Hypothesis 1: The development of new comparative advantages in a region is positively related to the relatedness of an industry to existing productive capabilities.**

At the NUTS2 level, confirmatory evidence is found that the patterns observed at the country level related to hypothesis 1 are robust (see Table 4.5). Neighbourhood density (dens) correlates significantly and robustly positive with RCA values in the short run. In order to improve its position in a given industry, it is supportive for a region to already have established industries requiring similar capabilities (see Schott 2004 or Hausmann and Klinger 2006). On the contrary, at the first glance the long-run relationship between neighbourhood density (dens_mean) and specialisation at the regional level is less clear-cut than at the country level. The coefficient switches from insignificant to either significantly positive or significantly negative. Positive results sometimes occur if interaction terms between neighbourhood density and capabilities (i.e. education and skills) and the size of the NUTS2 regions are not included. Including the interaction terms the effect is negative and robust. Anyway, the positive short-run effect dominates the negative long-run effect as the average partial effects are much higher in the short-run. Summarising the results for all specifications, the regressions at the regional level testing hypothesis 1 tend to be in line with what has been found for countries, in particular for the short run effects.

**Hypothesis 2: The development of new comparative advantages in a region is decreasing with the level of average sophistication of products.**

At first sight, the results for the relationship between average product sophistication and RCA values do not deliver conclusive evidence to support hypothesis 2 at the regional level. Any significant results are observable for short-run effects but effects are significantly positive in the long-run (see Table 4.5). Therefore, it seems that the results at the regional level are contradicting to those found at the national level. This contradiction is explained by differences in the calculation of the RCAs. In chapter 3, RCA values are calculated comparing national specialisation patterns across countries all over the world. In chapter 4, the analysis is restricted to the EU-28 due to data constraints. Furthermore, average product sophistication within a NACE 4-digit industry does not vary across regions within a country (as described above in section 4.1.2). As a result, the interpretation has to be different than for the country level. In this setting, the positive long-run effect hints at higher average concentration of industries in fewer regions where average product sophistication is higher. Hence, the empirical evidence is confirming hypothesis 2 that it is more difficult to develop new comparative advantage in more sophisticated technologies[51].

*Regional specialization patterns and the role of education and skills*

**Hypothesis 3: Knowledge capabilities increase the likelihood to develop new comparative advantages in a region.**

When analysing the effects of education and skills, the positive effect found at the country level is also found at the regional level. However, the pattern is less robust; insignificant coefficients and sometimes even negative long-run effects occur with respect to some skills variables (see Table 4.6 for a summary of results). However, interaction effects between those skills variables and neighbourhood density (see below) are always significantly positive. Furthermore, occurring negative long-run effects are dominated by positive short-run effects. Explaining industry shares within the EU, some of the education variables tested show a positive impact. However, ignoring a possible interaction between the education (and skills) indicators and the neighbourhood density the coefficients are often insignificant (compare Table 4.5 for tertiary educational attainment). Including interaction terms results in positive effects of the education and skills indicators but with negative interaction effects with neighbourhood density. All in all, the results found at the regional level seem to support the patterns observed at the country level (also see Krueger and Lindahl 2000 or Psacharopoulos and Patrinos 2004) although the evidence is less clear-cut.

**Table 4.6 Specialisation, product space and knowledge capabilities, industry level regressions, NUTS2 regions, alternative indicators measuring education, dep. variable = Standardised revealed comparative advantage (SRCA)**

| | Variable | | Interaction Term - Neighbourhood Density | | Interaction Term - Product Sophistication | |
|---|---|---|---|---|---|---|
| **Standardised revealed comparative advantage, srca** | Short Run | Long Run | Short Run | Long Run | Short Run | Long Run |
| population aged 25-64 with tertiary education attainment (Eurostat) | (+) | - | - | + | 0 | 0 |
| persons with tertiary educ. or empl. in science/tech, % of active pop. | (+) | +/- | - | + | 0 | 0 |
| people with tertiary educ. AND empl in science/tech, % of active pop. | (+) | +/- | - | + | 0 | 0 |
| persons with tertiary educ., in % of active pop. | (+) | +/- | - | + | 0 | 0 |
| persons employed in science/tech, in % of active pop. | (+) | +/- | - | + | 0 | 0 |
| persons with tertiary educ. OR empl. in science/tech, % of total empl. | (+) | (+) | - | + | - | 0 |
| people with tertiary educ. AND empl in science/tech, % of total empl. | (+) | (+) | - | + | - | 0 |
| persons with tertiary educ., in % of total empl. | + | +/- | - | + | - | + |
| persons employed in science/tech, in % total empl. | (+) | (+) | - | + | - | 0 |

*Note: + ... robustly sign. positive coefficient in all tested equations, (+) ... positive but not always significant, - ... robustly sign. negative coefficient in all tested equations, (-) ... negative but not always significant, 0 ... neither sign. positive nor negative results, +/- contradicting significant results depending on the specified equation*
*Source: WIFO calculations*

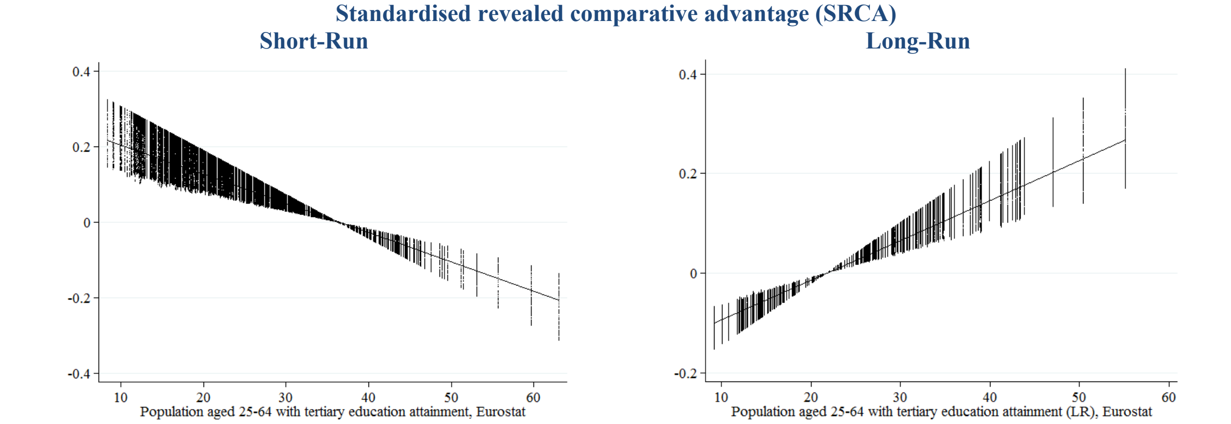
**Hypothesis 4: Knowledge capabilities allow escaping existing specialisation patterns.**

The results related to hypothesis 4 found at the country level are robustly confirmed at the regional level. For all skills and education indicators tested the interaction with neighbourhood density is robustly significantly negative in the short-run and positive in the long-run. While finding a negative long-run effect of neighbourhood

[51] See e.g. Hausmann and Klinger (2006) for a discussion about the relationship between structural transformation and produc space.

density on RCA as explained above, the overall partial effect turns positive given a minimum level of skills (compare Figure 4.4). This result adds to the conclusion drawn for the country level that although high levels of relatedness might increase sluggishness in productive structures they could be overcome by high levels of education.

**Figure 4.4 The effect of neighbourhood density on revealed comparative advantage depending on tertiary educational attainment, NUTS2 regions, NACE 4-digit industries.**

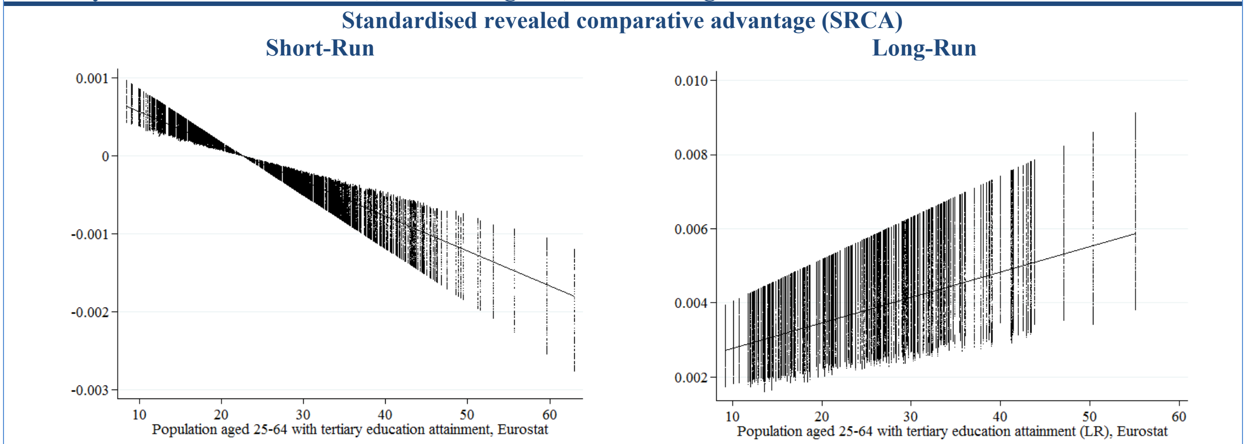



*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. Eurostat, BACI dataset (Gaulier and Zignago 2010), Bureau van Dijk (Amadeus)*

**Hypothesis 5: Knowledge capabilities facilitate the upgrading of the industry portfolio.**

Similar to the results from the regional analysis found for hypothesis 2, the evidence for hypothesis 5 is less conclusive than for the country level. For most of the skills and education indicators tested the interaction term with product sophistication is insignificant (compare Table 4.5 for tertiary educational attainment). Again, the lack of significance might be explained by the calculation of the average product sophistication of industries. Anyway, whenever coefficients for the interaction terms significantly deviate from zero, the sign is in line with the results found at the country level. Figure 4.5 illustrates the tendency of results. However, please note the small scale at the y-axis hinting at the low significance of the interaction terms. All in all, the data do not (or at best only slightly) confirm hypothesis 5, neither was found evidence that hypothesis 5 might be wrong.

**Figure 4.5 The effect of average product sophistication on revealed comparative advantage depending on tertiary educational attainment, NUTS2 regions, NACE 4-digit industries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. Eurostat, BACI dataset (Gaulier and Zignago 2010), Bureau van Dijk (Amadeus)*

*Regional specialization patterns and knowledge generation*

When looking at the impact of the relatedness to knowledge generating capabilities at the regional level, the results for patent neighbourhood density show some differences than what has been found for countries. These differences can be explained by differences in the level of aggregation in the data. While the analysis at the country level focuses at HS 6-digit level product classes, the heterogeneity across NACE 4-digit industries is lower. The caveat of the indicator on patent neighbourhood density related to the aggregation level is less severe for the regional level regressions. NACE 4-digit industries do not reflect the high heterogeneity across 6-digit product classes. The relatedness of patenting activities (aggregated to NACE 2-digit level) to NACE 4-digit industries is less overrated than the relatedness to HS 6-digit products. The long-run effect of patent neighbourhood density (see pat_dens_mean in Table 4.7) on RCA values is therefore positive (in opposite to the negative effect found at the country level) as would be expected from theoretical considerations. The more closely related an industry is to the regional patenting activities the more likely it is that the region has a comparative advantage in this industry. On the other hand, the short run is not significant (pat_dens).

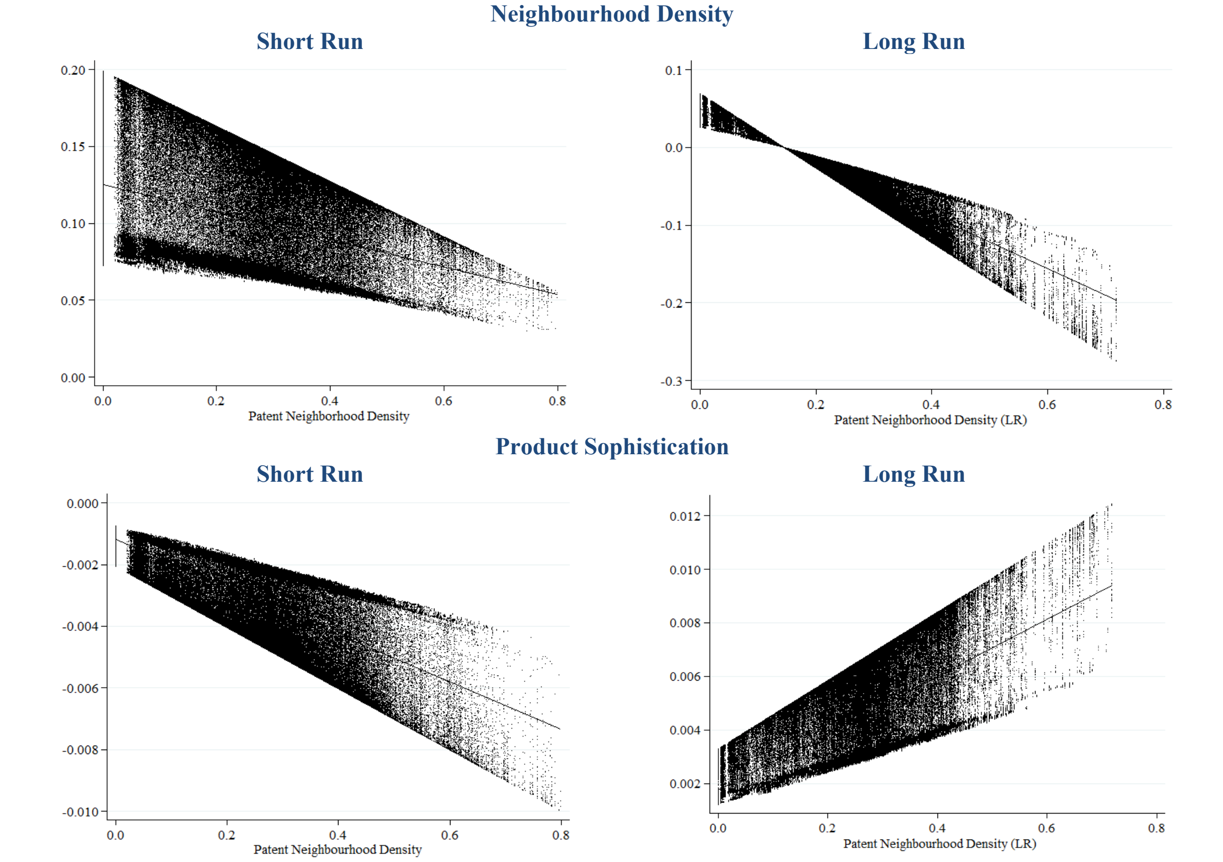
**Table 4.7 Specialisation, product space and knowledge generation, industry level regressions, NUTS2 regions, dependent variable = Standardised revealed comparative advantage (SRCA)**

| Model<br>Dependent Variable:<br>Standardised revealed comparative advantage, srca | (1)<br>APE<br>(p-value) | NUTS2 regions<br>QML Flogit Estimator<br>(2)<br>Sign | (3)<br>Sign | (4)<br>Sign |
|---|---|---|---|---|
| Lagged standardised revealed comparative advantage L.srca | 0.599 ***<br>(0.000) | +++ | +++ | +++ |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.092 ***<br>(0.000) | +++ | +++ | +++ |
| Neighbourhood density, dens | 0.101 ***<br>(0.000) | +++ | +++ | +++ |
| Neighbourhood density (LR), dens_mean | -0.019<br>(0.315) | ++ | 0 | ++ |
| Product sophistication, soph | -0.004 **<br>(0.039) | -- | 0 | 0 |
| Product sophistication (LR), soph_mean | 0.005 ***<br>(0.005) | +++ | 0 | 0 |
| Patent neighbourhood density, pat_dens | 0.002<br>(0.257) | +++ | 0 | +++ |
| Patent neighbourhood density (LR), pat_dens_mean | 0.014 ***<br>(0.000) | +++ | +++ | +++ |
| Interaction Neighb.density x Patent neighbourhood density | | --- | | --- |
| Interaction Neighb.density x Patent neighbourhood density (LR) | | --- | | --- |
| Interaction Prod. Soph. x Patent neighbourhood density | | | -- | --- |
| Interaction Prod. Soph. x Patent neighbourhood density (LR) | | | +++ | +++ |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |
| Regional Control Variables | YES | YES | YES | YES |
| Number of observations | 200,745 | 200,745 | 200,745 | 200,745 |
| Pseudo $R^2$ | 0.938 | 0.938 | 0.938 | 0.938 |
| Deviance | 10732 | 10707 | 10731 | 10706 |
| Log Pseudolikelihood | -49113 | -49101 | -49113 | -49101 |
| Wald-Test (Time Dummies) | 0.002 | 0.003 | 0.002 | 0.003 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

The interaction effect of product neighbourhood density and relatedness to patenting activities on specialisation reveals that the importance of capabilities from existing productive structures decreases for industries more closely related to the region's innovation activities (see upper left panel in Figure 4.6). As has been found for the country level, patenting activities reduce path dependency in productive structures. In the long run, patenting activities reinforce sluggishness in productive structures as firms focus their patenting activities in similar technology fields used for production (upper right panel in Figure 4.6)[52].

**Figure 4.6 The effect of product neighbourhood density and product sophistication on Standardised Revealed Comparative Advantage depending on patent neighbourhood density, NUTS2 regions, NACE 4-digit industries**




*Note : Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. OECD Regpat, AMADEUS (Bureau van Dijk), BACI dataset (Gaulier and Zignago 2010)*

Similarly to the product level regressions for countries, Figure 4.6 (lower left panel) shows a negative interaction effect between average product sophistication at the NACE 4-digit industry level and patent neighbourhood density on RCA values. Assuming that this finding is again (as for the country level) driven by those regions that are more distant to the technological frontier, it is in line with the product level regressions for countries. For catching-up regions, a higher relatedness to patenting activities implies that these activities are related to less sophisticated technology fields. On the contrary, in the long run regions are more likely to specialise in more sophisticated products if their patenting activities are closely related, while for the country level the opposite pattern has been observed. This deviation in results between the country and the regional level might be explained by the different level of aggregation (products vs. industries). It is more likely that average product sophistication calculated for NACE 4-digit industries for NUTS2 regions is more accurately linked to patenting activities as when calculated for HS 6-digit product classes. Therefore, the expected positive interaction term is observed for NUTS2 regions.

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52 For a discussion about product space and structural transformation see e.g. Hausmann and Klinger (2006), Hidalgo et al. (2007) or Cadot, Carrère and Strauss-Kahn (2011).

*Regional specialization patterns and knowledge inflows*

Analysing the relationship between knowledge inflows and specialisation patterns at the regional level is heavily limited by data constraints. Unfortunately, similarly to the country level, official statistics (e.g. Eurostat's FATS statistics) are not comprehensive enough to be used in the regression analyses. Regional trade statistics measuring knowledge inflows embodied in imports are also not available. The analyses are therefore restricted to the indicators based on the Amadeus firm-level data on FDI (and harmonised with official SBS statistics at more aggregated levels). In the following, the share of foreign owned firms in total manufacturing is used both at the country level (invariant across regions within a country) and at the regional level. Since the latter is less reliable due to the lack of representativity and the lower number of observations the country level indicator (i.e. share of foreign owned firms in the country) is used. Although the latter is less accurate for NUTS2 regions, the results are very robust independently of the indicator used.

The empirical results (see Table 4.8) are strongly in line with the results found for the country level. In particular very robust evidence is found for a positive impact of the overall presence of foreign owned firms in a country's manufacturing sector on specialisation (see e.g. Zahra, Ireland and Hitt 2000). The more foreign owned firms in a country, the higher specialised it is. In particular the average long-run partial effects are very high. On the other hand, the evidence on high shares of foreign owned firms in NACE 2-digit industries in the respective country is less clear-cut. Without including interaction terms with industry neighbourhood density no significant relationship between FDI and specialisation is observable. This is in line with Ning, Prevezer and Wang (2014), who find that the effects of FDI crucially depend on the diversification of the industrial structure. When including the interaction term, the same pattern is observed as for the country level. The difference in results between the country and the regional level might be explained by the construction of the indicator. While it is possible to compare the estimated industry aggregates on employment and value added based on Amadeus firm-level data with official statistics from Eurostat, it is not possible to correct any bias for the share of foreign owned firms at the regional level. The indicator is therefore prone to irresolvable noise in the data when calculating it at the NUTS2 level for NACE 2-digit industries. The analysis is therefore restricted to country level data which does not vary across regions by definition. This lack of variation seems to turn the significant results found at the country level insignificant at the regional level. However, when including the interaction terms with neighbourhood density, completely the same patterns are observed as at the country level (for both the FDI variable itself and its interaction with neighbourhood density). It therefore renders reasonable to use the country-level indicators also for analysing specialisation patterns at the regional level.

**Table 4.8 Specialisation, product space and the share of foreign owned firms in total employment (manufacturing), industry level regressions, NUTS2 regions, dependent variable = Standardised revealed comparative advantage (SRCA)**

| | | NUTS2 regions QML Flogit Estimator | | | | NUTS2 regions QML Flogit Estimator | | |
|---|---|---|---|---|---|---|---|---|
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** | **APE** | **Sign** | **Sign** | **Sign** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | | | | **(p-value)** | | | |
| Lagged standardised revealed comparative advantage L.srca | 0.590 *** (0.000) | +++ | +++ | +++ | 0.588 *** (0.000) | +++ | +++ | +++ |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.087 *** (0.000) | +++ | +++ | +++ | 0.088 *** (0.000) | +++ | +++ | +++ |
| Neighbourhood density, dens | 0.105 *** (0.000) | +++ | +++ | +++ | 0.102 *** (0.000) | +++ | +++ | +++ |
| Neighbourhood density (LR), dens_mean | -0.009 (0.619) | --- | 0 | --- | -0.007 (0.687) | --- | 0 | --- |
| Product sophistication, soph | -0.001 (0.446) | 0 | 0 | 0 | -0.001 (0.458) | 0 | ++ | ++ |
| Product sophistication (LR), soph_mean | 0.005 *** (0.001) | +++ | 0 | 0 | 0.005 *** (0.001) | +++ | 0 | 0 |
| Foreign owned companies (share in manufacturing) | 0.114 *** (0.007) | +++ | +++ | +++ | | | | |
| Foreign owned companies (share in manufacturing, LR) | 8.538 *** (0.000) | +++ | +++ | +++ | | | | |
| Interaction Neighb.density x For. owned comp. (manufacturing) | | --- | | --- | | | | |
| Interaction Neighb.density x For. owned comp. (manufacturing, LR) | | +++ | | +++ | | | | |
| Interaction Prod. Soph. x For. owned comp. (manufacturing) | | | 0 | 0 | | | | |
| Interaction Prod. Soph. x For. owned comp. (manufacturing, LR) | | | + | + | | | | |
| Foreign owned companies (share in NACE-2dig) | | | | | 0.016 (0.354) | +++ | 0 | +++ |
| Foreign owned companies (share in NACE-2dig, LR) | | | | | 0.008 (0.628) | --- | 0 | --- |
| Interaction Neighb.density x For. owned comp. (NACE-2dig) | | | | | | --- | | --- |
| Interaction Neighb.density x For. owned comp. (NACE-2dig, LR) | | | | | | +++ | | +++ |
| Interaction Prod. Soph. x For. owned comp. (NACE-2dig) | | | | | | | --- | --- |
| Interaction Prod. Soph. x For. owned comp. (NACE-2dig, LR) | | | | | | | ++ | ++ |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Regional Control Variables | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 212,719 | 212,719 | 212,719 | 212,719 | 211,910 | 211,910 | 211,910 | 211,910 |
| Pseudo $R^2$ | 0.938 | 0.938 | 0.938 | 0.938 | 0.938 | 0.938 | 0.938 | 0.938 |
| Deviance | 11494 | 11489 | 11493 | 11488 | 11445 | 11442 | 11444 | 11441 |
| Log Pseudolikelihood | -50695 | -50693 | -50695 | -50692 | -50441 | -50440 | -50441 | -50439 |
| Wald-Test (Time Dummies) | 0.002 | 0.001 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively: ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

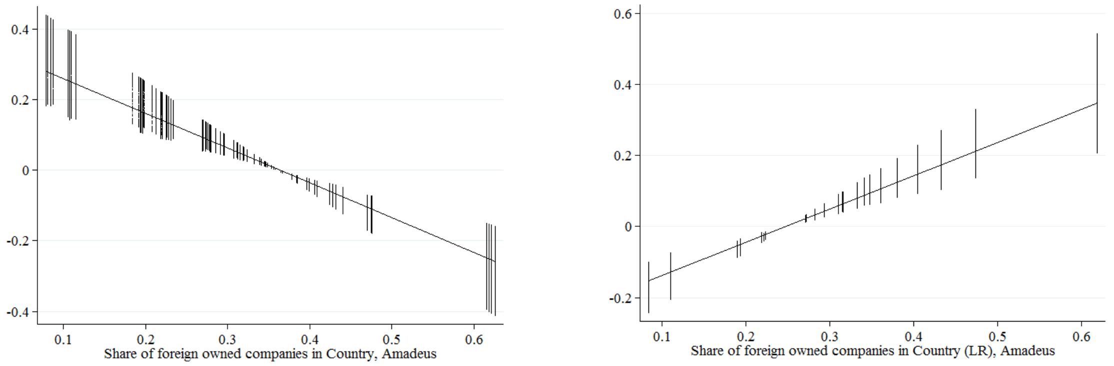
In addition the share of foreign owned firms within NUTS2 regions is also tested but the effects are insignificant except in the case when the interaction term with neighbourhood density is included. However, as explained above this indicator might have low reliability. Anyway very similar (and significant) patterns are observable for the interaction terms with neighbourhood density when comparing it with the other indicators used at the regional (compare Figure 4.7) or at the country level (see chapter 3).

Figure 4.7 graphically summarises the partial effects of neighbourhood density on specialisation as observed in the data. As described in Box 3.1, the figure illustrates the impact of neighbourhood density on RCAs for each observation taking into account all other variables controlled for. As effects based on the observed data are plotted, the figures only take values at x-axis that are also appearing in the data. Obviously, more variation is found at the x-axis for more disaggregated indicators. For instance, the share of foreign owned firms can take more values if calculated at the NACE 2-digits level instead of the country level only. Anyway, the patterns are very similar independent of the level of disaggregation and are very robust across different specifications. Also changing the set of regional control variables does not change the picture. The results therefore strongly support the conclusion in chapter 3 that FDI helps tapping into new industries that are less close to a country's or region's product space. Foreign owned firms therefore potentially support escaping from structurally predetermined paths more easily in the short run. On the other hand, also for regions holds that in the long run foreign owned firms tend to focus their activities in those countries that fit their requirements best. This leads to higher concentration of regions into more closely related industries (see e.g. De Propris and Driffield 2006).

**Figure 4.7 The effect of neighbourhood density on revealed comparative advantage depending on the share of foreign owned firms, NUTS2 regions, NACE 4-digit industries**

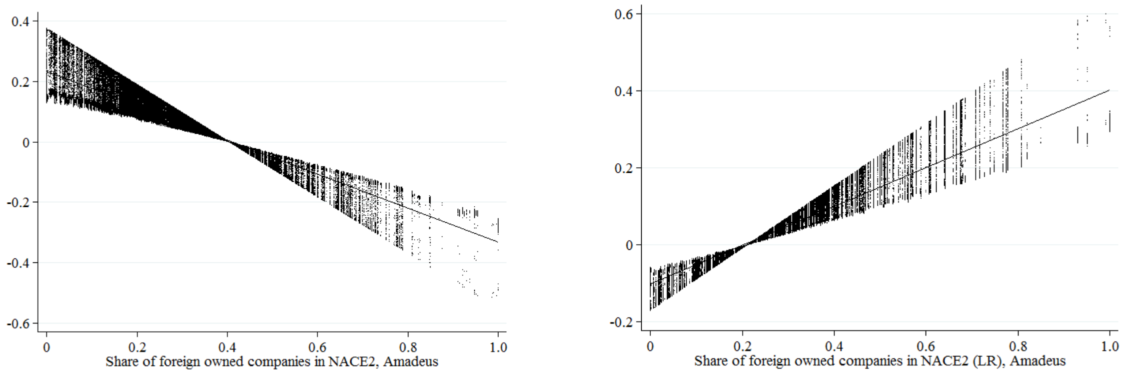
**Share of foreign owned firms in total manufacturing (country)**

**Short-Run** **Long-Run**



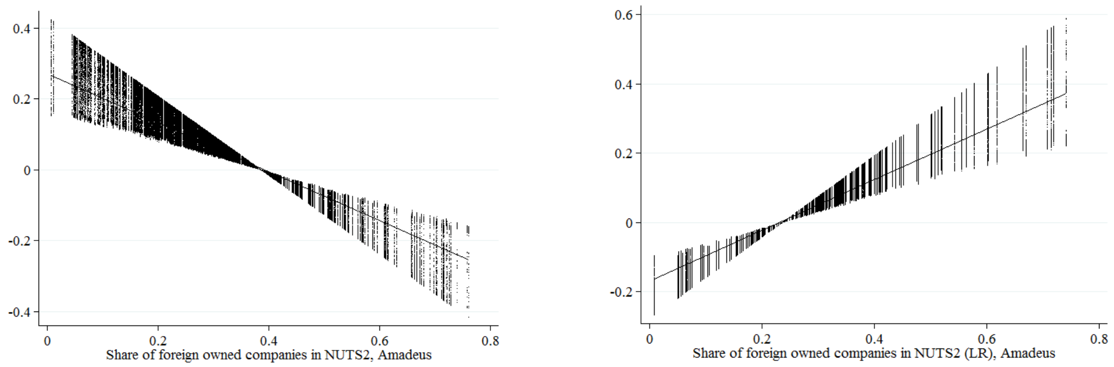

**Share of foreign owned firms in NACE 2-digit industry**

**Short-Run** **Long-Run**




**Share of foreign owned firms in total manufacturing (NUTS2 region)**

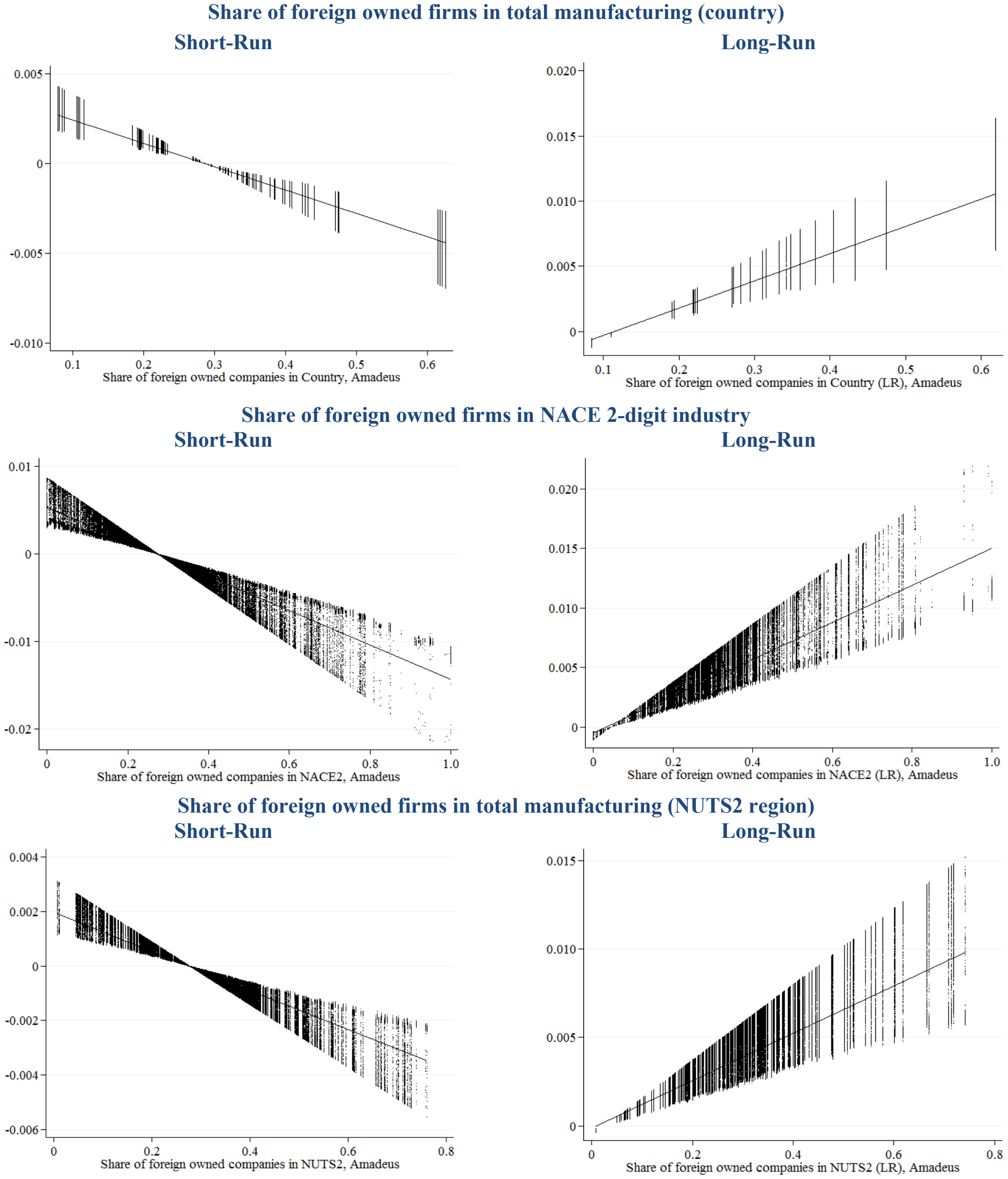
**Short-Run** **Long-Run**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. Eurostat, Bureau van Dijk (Amadeus)*

The results for the interplay between product sophistication and inward FDI activities on specialisation are less conclusive at the regional level. While in chapter 3 evidence is found that countries with higher shares of foreign owned firms in the long run tend to specialise in more sophisticated products than comparable countries with less inward FDI, only very weak evidence is observable at the regional level. In almost all specifications using the share of foreign owned firms in manufacturing either at the country or the NUTS2-level insignificant results appear for the interaction terms. However, whenever a long-run coefficient is significantly different from zero its sign is positive. For the short run not many significant results occur. Nevertheless, although coefficients are often insignificant their sign is always negative as observed in chapter 3 for countries. Looking at the corresponding p-values shows that they are often close to the 10% confidence interval.

**Figure 4.8 The effect of average product sophistication on revealed comparative advantage depending on the share of foreign owned firms, NUTS2 regions, NACE 4-digit industries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. Eurostat, Bureau van Dijk (Amadeus)*

Standing alone this might appear irrelevant if complying with the standard rules for interpreting test statistics. Nonetheless the results fit to the pattern not only observed at the country level but also found for FDI at NACE 2-digits level. For this indicator (see the two panels in the middle of Figure 4.8) the significant interaction effects (positive in the short run and negative in the long run) are very robust across all specifications tested. The results described in the paragraph above might therefore be taken as additional confirmation of a robustly observed pattern. Inward FDI tends to improve the product portfolio of a country in the long run, however not in the short run. At first foreign owned firms produce less sophisticated products and only after a while they extend their portfolio to more sophisticated products or even R&D activities.

## 4.3. SUMMARY – COMPARING COUNTRY- AND REGIONAL-LEVEL ANALYSES

Comparing the empirical evidence stemming from the analyses (i) at the country level (presented in chapter 3) and (ii) at the regional level (chapter 4) several differences and limitations in the data sets have to be taken into account. All in all, the results are quite similar while some of the significant differences might be explained by the different data sets. In some cases, differences occur in the sign of coefficients which at first glance appear contradicting. However, these findings do not contradict each other but are the result of a slightly different set up of the regressions. The main differences between the two levels of analyses are:

- Regions vs. countries: Regions tend to be more heterogeneous than countries. For instance, differences between urban and rural regions at the regional level have to be controlled for. Although country characteristics, of course, can vary, additional control variables have been included for regional characteristics in the analyses at the NUTS2 level. Anyway, the approach using country fixed effects (incl. regional control variables for the regional analyses) seems to filter out all relevant characteristics of countries and regions.
- Products (HS 2002 6-digits) vs. industries (NACE Rev. 2 4-digits): Due to data constraints at the regional level, some of the indicators used at the country level are not available at the regional level. Furthermore, some of the indicators slightly differ due to issues of aggregation. For instance it had to be assumed that average product sophistication of NACE 4-digit industries does not vary across regions within a country. Using these country averages also for the analyses at the NUTS2 regional level is therefore less accurate. The results described above have also shown that the effect of product sophistication on specialization patterns is less strong at the regional level. However, this finding might be explained by the different data (production structures measured in terms of employment vs. export structures) used for calculating RCAs.
- Time frame: The main boundary constricting the time frame of the analyses in this study are structural breaks due to changes in classification schemes for industries and products. While for the country level the focus was on trade data based on the harmonized system of product categories (HS), at the regional level the analyses hat to stick to industry level data. In the former, using the HS-version from 2002 allowed to investigate a time frame of 10 years. On the other hand, the change from NACE Rev 1.1. to NACE Rev. 2 restricts the regional analyses to the years 2008 to 2012. Therefore, the time frame is much shorter for the regional level analyses and also coincides with the years of the economic crisis and beyond. Nevertheless, since results are quite similar for both samples (or at least no hints are found that they contradict each other) the crisis seems affecting the investigated relationships only negligibly in the short run. However, given the short time frame covered in the analysis potential crisis effects in the medium run are unobserved.
- World market shares vs. EU industry share: One major drawback of the different data sets is their incompatibility when looking at market shares. While it is possible to calculate the world market shares for countries (based on trade data), the regional EU industry shares are not meaningful for investigating specialization patterns. At least, the two different shares are not comparable. However, the issue does not occur for analyzing revealed comparative advantage. Analyzing regional EU industry shares is therefore skipped.

Considering the differences mentioned above, the results found at the regional level are very similar to those found at the country level. In some cases, the evidence is less clear-cut at the regional level. Table 4.9 summarises the results of chapters 2 and 4. In both analyses very robust evidence of persistency in specialisation patterns is found (see e.g. Benedictis 2005 or Amador, Cabral and Maria 2011). Average partial effects show even higher persistency at the regional level although its time frame coincides with the years after the economic crisis.

Very robust evidence is also found for the importance of relatedness to already existing productive structures. The indicator neighbourhood density is robustly positively correlated with specialisation patterns (see e.g. Breschi, Lissoni and Malerba 2003 or Hausmann and Klinger 2006). Although evidence is less robust at the regional level, taken together it provides a homogeneous picture. Strong hints are also found for sluggishness in economic structures (see e.g. Antonelli 2006, Koo 2007 or Hausmann, Hwang and Rodrik 2007) whereby the evidence is less clear-cut at the regional level but tends to be in line with the country level results.

The indicator measuring the sophistication of products unfortunately turned out to be less meaningful at the regional level. As it is not possible to observe differences in average product sophistication at NACE 4-digit level for regions within countries, the variation within this variable is too low for conclusive findings. Anyway, the regional level evidence at least does not refuse the hypothesis that it is more difficult to specialise in more sophisticated product. If significant results are found for NUTS2 regions, they point into the same direction as at the country level.

**Table 4.9 Comparing empirical evidence between the country and the regional level**

| | Country | NUTS2 |
|---|---|---|
| **Persistency in specialisation patterns** | | |
| Comparative advantages and industry structures are highly persistent over time. | +++ | +++ |
| **Product relatedness and comparative advantage** | | |
| High degrees of product relatedness support developing new or improving existing comparative advantage in closely related technologies. | +++ | +++ |
| High product relatedness evokes sluggishness in economic structures limiting structural adjustments. | +++ | + |
| **Product sophistication and comparative advantage** | | |
| The higher the sophistication of products, the lower the number of countries exporting a product. | +++ | + |
| The closer countries are to the technological frontier the more competitive and specialised they are in more sophisticated products. | ++ | n.a. |
| **Knowledge capabilities and comparative advantage** | | |
| Knowledge capabilities favour the development of new and deepening existing specialisations. | +++ | ++ |
| Higher knowledge capabilities reduce the sluggishness in industry structures by reducing the importance of already existing related capabilities to develop new comparative advantage | +++ | +++ |
| Education and skills reduce difficulties to specialise in more sophisticated products. | ++ | (+) |
| **Knowledge generation and comparative advantage** | | |
| Patenting activities reduce path dependency in productive structures, ... | +++ | +++ |
| … but a higher degree of relatedness of an industry to the countries patenting activities also reinforces sluggishness in productive structures. | +++ | +++ |
| The more closely related an industry is to local patenting activities the more likely it is that the region/country has a comparative advantage in this industry. | 0 | ++ |
| A high relatedness to local patenting activities helps specialising in more sophisticated related products in particular for the most advanced countries. | +++ | n.a. |
| Regions /countries are more likely to specialise in more sophisticated products if their patenting activities are closely related. | (-) | ++ |
| **Knowledge inflows via FDI** | | |
| Higher shares of FDI positively affect the economy as a whole through knowledge spillovers from foreign owned firms to other industries. | +++ | +++ |
| High shares of foreign owned firms within the sector seem to support gaining market shares and specializing in the respective sector only in the short run. | +++ | +++ |
| In the long run higher shares of foreign owned firms within an industry tend to reduce comparative advantage. | +++ | +++ |
| Catching up countries benefit more from spillovers from foreign owned firms than the most advanced countries. | ++ | n.a. |
| In the short run, foreign firms support countries/regions tapping new technology fields that are less closely related to already existing productive structures, ... | +++ | +++ |
| … but in the long run inward FDI reinforces existing specialisation. | +++ | +++ |
| In the long run, foreign owned firms affect the upgrading of the product portfolio … | | |
| … positively in general. | ++ | 0 |
| … less favourably for the most advanced EU member states. | ++ | n.a. |
| In the short run, for the average sophistication of the product portfolio higher shares of FDI are … | | |
| … in general less favourable. | ++ | 0 |
| … positive for the most advanced EU member states. | ++ | n.a. |
| **Knowledge inflows embodied in imports** | | |
| Importing more sophisticated capital goods helps overcoming specialisation patterns but enforces them if it is maintained over a long time period. | +++ | n.a. |
| Importing more sophisticated capital goods or industry supplies over a long time period can … | +++ | n.a. |
| … either help upgrading a country's product portfolio, … | +++ | n.a. |
| … or reinforce structural traps if they substitute domestic production. | +++ | n.a. |

*Note: +++ ... very robust and significant evidence, ++ ... strongly significantly confirmed, + confirmed, + ... slightly confirmed, (-) ... slightly rejected, 0 ... inconclusive evidence, n.a. ... not applicable*
*Source: WIFO calculations*

Robust evidence is found at both levels of analysis for the importance of education and skills on specialisation (see Cohen and Levinthal 1990 or Zahra and George 2002). This holds for both developing new or deepening existing specializations but also for reducing the importance of already existing related capabilities. The importance of education and skills for upgrading the product portfolio is only confirmed at the national level. At the regional level only minor hints for the correctness of this hypothesis are found.

Some differences have been found for the indicator approximating the relatedness of knowledge generation capabilities. Most of the differences can be explained by the level of aggregation in the data. The caveat of the indicator on patent neighbourhood density related to the aggregation level is less severe for the regional level regressions. The evidence robustly shows for both levels of analyses that a high degree of relatedness to domestic patenting activities reinforces sluggishness in productive structures. The positive short run impact of closely related patenting activities allowing tapping new fields of technology is only confirmed at the regional level. Furthermore, while regions are more likely to specialise in more sophisticated products if their patenting activities are closely related, for the country level the opposite pattern has been observed. However, this contradicting evidence is mainly explained by limitations of the indicator.

Comprehensive consensus between the regional and the country level is also found for the importance of inward FDI for specialisation patterns. For both levels of aggregation positive impacts of higher shares of foreign owned firms on the total economy are found. Moreover, the industry with high FDI shares only benefits in the short run while in the long run comparative advantage is reduced by higher FDI shares in the industry. Furthermore, both the national and the regional level analyses show that FDI helps tapping technology fields that are less closely related to existing productive structures. Moreover, also the reinforcing effect of FDI on existing specialisation patterns is confirmed at the regional level. On the contrary, the evidence what concerns the interplay between FDI and an upgrading of the product portfolio is inconclusive. The robust findings at the country level are not evident in NUTS2 regions but at least they do not contradict the country level findings. Further indicators measuring knowledge inflows (e.g. imports of capital goods or industry supplies) are not available at the regional level.

Chapter 5.

# RELATEDNESS AND DIVERSIFICATION IN PRODUCTION AND KNOWLEDGE, PRODUCT SOPHISTICATION AND ECONOMIC PERFORMANCE AT THE REGIONAL LEVEL

This chapter analyses the impact of relatedness and diversification of the regional production structure and knowledge base on European regional economic performance. Hence it complements the previous parts of this study - which assessed the drivers of developing successful new specialisations in trade and industry at the country and regional levels - by examining the effect of regional specialisation and diversification patterns on aggregate economic performance. The chapter focuses on the impact of related and unrelated variety in production and knowledge on regional employment growth, providing empirical evidence on the concepts of related diversification and regional branching (Boschma and Frenken 2011) that underlie the Smart Specialisation Strategies of the European Union. In addition, this chapter investigates the effect of regional product sophistication, which captures the depth and breadth of the regional knowledge base, on economic performance. Compared to chapter 4, where this indicator is employed at the 4-digit industry level, here an aggregate regional measure is used.

The first section below provides the conceptual background for the empirical analysis undertaken. It explains the link between the measures of relatedness in the regional production structure employed here and the product space indicators used in previous chapters where the focus lies on traded manufacturing goods (chapters 2 and 3) and the disaggregated industry level (chapter 4). The extension of the concepts of related and unrelated variety to regional knowledge-generating capabilities is outlined and further variables included in the analysis are discussed. The next section provides a description of the main indicators and their distribution across the European NUTS2 regions. Section 5.3 summarises the main hypotheses to be tested as well as the empirical approach and then presents and discusses the estimation results, while the final section concludes.

## 5.1. CONCEPTUAL BACKGROUND TO CHAPTER 5

The focus of this chapter is on assessing the relationship between the characteristics of regional production structures and knowledge capabilities on the one hand and regional economic performance at the aggregate level on the other. Thus the analysis moves beyond the disaggregated product and industry level employed in the previous chapters and therefore also uses measures of relatedness and diversity that are more suited to the aggregate level than measures based on the product space. The indicators employed in this chapter, related and unrelated variety, are concerned with the diversity of economic activities in terms of the industries present in a region and with their technological proximity. These indicators can be extended to regional knowledge-generating capabilities, and their effect on regional employment growth is then estimated econometrically.

A key reason why the presence of a variety of economic activities in a region should be beneficial to growth are the advantages of knowledge spillovers between a diverse mix of industries, which provide opportunities for learning new ways to solve problems by recombining knowledge from different sources (Jacobs 1969). Knowledge flows operate between industries for example through formal or informal networks and the mobility of employees or co-operation and exchange between firms. Particularly new industries at an early stage of product development have been shown to benefit from access to a variety of local knowledge sources, while more mature industries should benefit more from a specialised environment offering access to industry-specific know-how (Duranton and Puga 2001; Neffke et al. 2011).

Recently, it has been argued that knowledge spills over more easily between industries that are technologically related than between unrelated ones sharing less common knowledge (Frenken, Van Oort and Verburg 2007). Hence, the presence of a variety of related sectors in a region should have a stronger growth-enhancing effect than a variety of unrelated sectors. Unrelated variety can, however, still play an important role for regional economic performance by moderating economic shocks. Regional diversification across a portfolio of (unrelated) industries provides a buffer against the contraction of a particular sector, which would hit those regions harder that are characterised by a greater variety of industries related to that sector.

Variety can be measured not only in terms of the regional production structure, but also regarding the knowledge-generating or innovative capabilities a region possesses, captured for instance by patenting activities (Castaldi, Frenken and Los 2015). Similar to the argument for industries, a greater technological diversity of regional innovative activities is expected to positively affect economic performance, since variety creates opportunities for cross-fertilisation and recombinations of diverse knowledge into innovations. Again, a variety of related knowledge capabilities is thought to facilitate the absorption of knowledge spillovers and therefore innovation and growth in general since researchers in related fields share a common cognitive framework. Related variety thus contributes to growth by fostering incremental innovation within narrow technological domains. Unrelated variety, on the other hand, has the potential to give rise to radical or breakthrough innovations through the combination of previously unrelated technological approaches. If successful, this can create entire new industries and therefore contribute substantially to employment growth in the long term (Saviotti and Frenken 2008).

### 5.1.1. Measuring related and unrelated variety in regional production and knowledge

To measure related and unrelated variety in regional production structures, the approach implemented in this chapter follows Frenken, Van Oort and Verburg (2007), who identify relatedness by using the structure of the NACE classification. While the 2-digit NACE sectors are assumed to be unrelated to each other, the 4-digit industries within each 2-digit sector are assumed to be related. Variety is then measured using the distribution of regional economic activity - proxied by employment in this chapter - across and within NACE 2-digit sectors, for instance using Shannon's index of information entropy. Box 5.1 explains this approach in more detail.

**Box 5.1 Related and unrelated variety in production**

Let $\mathrm{E}_{\mathrm{s,r}}$ denote employment in NACE 2-digit sector s in region r, so that the share of 2-digit sector s in total regional employment is given by $\mathrm{E}_{\mathrm{s,r}}/\mathrm{E}_{\mathrm{r}}$. Unrelated variety in production in region r is then measured by the Shannon entropy over the region's employment shares in the 2-digit sectors:

(F20) $UV_r^P = \sum_{s=1}^{S} \frac{E_{s,r}}{E_r} \log_2 \left(\frac{E_r}{E_{s,r}}\right)$, where $S$ is the total number of 2-digit sectors.

This measure reaches its minimum of zero when all regional employment is concentrated in one 2-digit sector and its theoretical maximum of $\log_2 (S)$ when a region's employment is equally distributed across all 2-digit sectors.

Further, let $\mathrm{E}_{\mathrm{i,s,r}}$ denote employment in NACE 4-digit industry i belonging to sector s in region r, so that the regional employment share of industry i in sector s is given by $\mathrm{E}_{\mathrm{i,s,r}}/\mathrm{E}_{\mathrm{s,r}}$. Related variety in production in region r is then measured by the weighted sum of the entropy of employment shares across the 4-digit industries within each 2-digit sector:

(F21) $RV_r^P = \sum_{s=1}^{S} \frac{E_{s,r}}{E_r} \cdot H_{s,r}^P$

where $H_{s,r}^P = \sum_{i=1}^{I} \frac{E_{i,s,r}}{E_{s.r}} \log_2 \left(\frac{E_{s,r}}{E_{i,s,r}}\right)$ and $I$ is the number of 4-digit industries within each 2-digit sector.

This measure takes on its minimum of zero if regional employment within each 2-digit sector is entirely concentrated in one 4-digit industry and its theoretical maximum if employment is equally distributed across the 4-digit industries of that 2-digit sector with the largest number of 4-digit industries. The theoretical maximum is equal to $\log_2(I_{\max})$, where $I_{\max}$ is the maximum number of 4-digit industries within 2-digit sectors.

To measure related and unrelated variety in regional knowledge-generating capabilities, the approach for sectors of production is applied to regional patent applications to the European Patent Office using the structure of the International Patent Classification (IPC). The 3-digit technology classes in the IPC are assumed to be unrelated to each other, while the 7-digit subclasses within each 3-digit class are assumed to be related. In choosing these disaggregation levels, the aim was to keep the approach comparable to that for sectors of production using the NACE classification.[53] Since observations on regional patent applications are low and variable from year to year for some regions, especially at the 7-digit disaggregation level of technology fields, a discounted sum of patent applications back until 1990 is constructed as a first step for each region. This reflects the continued but declining value of past innovations for the regional knowledge base (a discount factor of 0.8 is assumed).[54] Box 5.2 outlines the construction of measures of related and unrelated variety in knowledge capabilities based on the patent or knowledge stocks thus constructed.

[53] The top level in the IPC consists of eight technology fields from human necessities via chemistry and textiles to engineering and physics. The next level below is the 3-digit level, similar to the 2-digit level in the NACE. Two levels below the 3-digit level in the IPC is the 7-digit level, thus resembling the 4-digit level in the NACE.

[54] The patent stock at time *t* is calculated as $P_t = \sum_{s=0}^{S_{MAX}} \delta^s P_{t-s}$, where *s* denotes observations on patent applications dating before the current period *t* back to 1990, so its maximum ($S_{MAX}$) ranges between 29 for *t*=2008 and 32 (*t*=2011). $\delta$ is a discount factor assumed to equal 0.8.

**Box 5.2 Related and unrelated variety in knowledge generation**

Let $P_{c,r}$ denote the stock of patents filed by region $r$ in 3-digit IPC class $c$, and $P_{s,c,r}$ the stock of patents in 7-digit subclass $s$ belonging to 3-digit class $c$. If $P_r$ is the total stock of patents in all IPC classes in region $r$, unrelated variety in knowledge generation in region $r$ is measured by the entropy over the region's patent shares in the 3-digit IPC classes:

(F22) $UV_r^K = \sum_{c=1}^{C} \frac{P_{c,r}}{P_r} \log_2 \left(\frac{P_r}{P_{c,r}}\right)$, where $C$ is the total number of 3-digit IPC classes.

This measure reaches its minimum of zero when all regional patenting is concentrated in one 3-digit class and its theoretical maximum of $\log_2(C)$ when a region's patents are equally distributed across all 3-digit technology classes.

Related variety in knowledge generation in region r is measured by the weighted sum of the entropy of the region's patent shares over the 7-digit subclasses within each 3-digit IPC class:

(F23) $RV_r^K = \sum_{c=1}^{C} \frac{P_{c,r}}{P_r} \cdot H_{c,r}^K$

where $H_{c,r}^K = \sum_{j=1}^{J} \frac{P_{s,c,r}}{P_{c,r}} \log_2 \left(\frac{P_{c,r}}{P_{s,c,r}}\right)$ and $J$ is the number of 7-digit subclasses within each 3-digit IPC class.

This measure takes on its minimum of zero if regional patenting within each 3-digit class is entirely concentrated in one 7-digit subclass and its theoretical maximum if patents are equally distributed across the 7-digit subclasses of that 3-digit class with the largest number of 7-digit subclasses. The theoretical maximum is equal to $\log_2(J_{max})$, where $J_{max}$ is the maximum number of 7-digit subclasses within 3-digit IPC classes.

### 5.1.2. Controlling for localisation and urbanisation externalities

In addition to the benefits of the presence of a variety of economic activities in a region for regional employment growth - whether in related or unrelated industries - there are also advantages to the specialisation of a region in a particular industry and to urbanisation. The localisation of many firms of the same industry in one region facilitates access to specialised labour and intermediate input suppliers as well as intra-sectoral knowledge spillovers. To control for such localisation economies, a measure of regional specialisation in NACE 2-digit sectors relative to the EU as a whole is included. This is constructed from the location quotients of 2-digit sectoral employment, as described in Box 5.3.

**Box 5.3 Regional specialisation**

If the share of 2-digit sector s in total regional employment is given by $E_{s,r}/E_r$ and the share of sector s in total employment across all EU regions in the sample is given by $E_s/E$, the location quotient of relative specialisation of a region r in sector s is defined as:

(F24) $LQ_{s,r} = \frac{E_{s,r}/E_r}{E_s/E}$

The location quotient measures the share of regional employment in 2-digit sector s relative to the share of this sector in total EU employment. It takes values less than, equal to or greater than 1 if region r is less, equally or more specialised in sector s than the EU as a whole. The location quotients for all sectors in region r are then summed and averaged to obtain a measure of regional specialisation.

On the other hand, urbanisation economies are available to firms of all sectors and result from the concentration of economic activity independent of its sectoral composition. They may arise from, for example, the existence of superior infrastructure, universities, government institutions and trade associations and networks. To control for urbanisation economies, the population density of a region is included as a control variable. This equals total regional population divided by regional land area.

### 5.1.3. Accounting for regional heterogeneity

The European regions differ in terms of their level of technological development and hence their industrial structure. In particular, the Central and Eastern European Member States (EU-12) underwent massive structural change since the mid-1990s with the transition from the planned communist to a market-based economic system and EU accession in the 2000s. Their catching-up process involved the decline of old monopolies and the emergence of a multitude of new firms in new sectors (e.g. services). By means of large inflows of FDI, the EU-

12 also established themselves as suppliers of intermediate inputs in European and global production chains. By comparison, industries in the Member States from Western Europe (EU-15) are more mature and closer to the technological frontier. Diversification into less related industries could therefore be a stronger growth driver in the regions of the EU-12 - or more generally, further from the technological frontier - where industries are at an earlier stage of their life cycle than in Western Europe and therefore benefit from spillovers from unrelated industries (cf. Neffke et al. 2011). In this view, regions closer to the frontier would benefit from related variety. Alternatively, as argued by Saviotti and Frenken (2008), long-term growth stems from the recombination of previously unrelated knowledge creating entirely new goods and industries, which is likely to be more effective closer to the technological frontier where the required advanced cognitive and technological capabilities are available (Krueger and Kumar 2004). Thus, unrelated variety could also be a growth driver for regions closer to the frontier. To examine these effects, an indicator on regional distance to the technological frontier is constructed using a regional classification from the EU Regional Innovation Scoreboard, which groups the NUTS2 regions into innovation leaders, innovation followers, moderate and modest innovators.

An additional differentiation of the regions that is investigated is their degree of urbanisation. Highly urbanised areas tend to be characterised by greater sectoral diversity, inspiring Jacobs (1969) to formulate her original hypothesis on the growth benefits of local variety in cities. Combined with the life-cycle view of industrial development, this implies that industries at an early stage of their life cycle benefit from locating in diverse cities, while at later stages, firms benefit from locating in more specialised cities, which are often smaller and located more peripherally than the dominant metropolitan agglomerations (Duranton and Puga 2001; Neffke et al. 2011). Hence, employment growth in more urbanised regions could be expected to be driven by general or unrelated variety, while in intermediate or less urbanised regions, related variety or specialisation should play a stronger role. Van Oort, de Geus and Dogaru (2014) indeed find a significant positive effect of related variety on employment growth for small- and medium-sized EU city-regions and no significant effect of either related or unrelated variety for large and capital regions. On the other hand, in their study of Austrian NUTS3 regions, Firgo and Mayerhofer (2015) find that unrelated variety has a stronger positive effect for rural and industrialised regions, while related variety matters more for employment growth in urban regions. In this report, the regional degree of urbanisation is measured by the share of households living in areas with high, intermediate and low population density.

## 5.2. DATA AND INDICATORS USED IN CHAPTER 5

The main measure of regional economic performance employed in this chapter is employment growth, on which data are obtained for the total economy and manufacturing up to 2011 from the Cambridge Econometrics European Regional Database (2014 update). This source also provides data on employee compensation, hours worked and gross fixed capital formation, from which additional variables are constructed to control for the regional wage rate, investment per worker and the share of manufacturing in total employment. The last variable is included to account for differences in the sectoral composition of regional economies.

The key explanatory variables of interest are measures of related and unrelated variety in production and knowledge as well as regional product sophistication. The variety indicators for production are computed using data on regional employment in 2- and 4-digit industries (NACE Rev. 2) constructed from Bureau van Dijk's AMADEUS database as well as Eurostat, as described in section 4.1.1 of the report. Since these variables are available from 2008 onwards, the analysis in this chapter covers the years from 2008 to 2011. The regional specialisation measure is also constructed based on these data. The indicators on knowledge variety are computed using data on regional patent applications to the European Patent Office taken from the OECD REGPAT database. The patent applications are counted by priority year and allocated to the regions according to place of residence of the applicant. Patents with applicants from several regions are divided equally among these (fractional counts). For regional product sophistication, the data at the 4-digit industry level described in section 4.1.2 of this study are aggregated to the regional level using the shares of each 4-digit industry in total regional employment. Finally, data on population density are taken from Eurostat.

The indicator on regional distance to the technological frontier is constructed using information from the Regional Innovation Scoreboard 2014,[55] which groups the NUTS2 regions into innovation leaders, innovation followers, moderate and modest innovators for the years 2008 and 2010. The value zero is assigned to regions at the frontier (innovation leaders) and the value three for regions furthest away from it (modest innovators). Regions at the frontier are from Germany, Denmark, Finland, Sweden and the UK; regions furthest away from it are from Bulgaria, Hungary, Romania and Poland. In between, regions from Austria, Belgium, France, the

[55] http://ec.europa.eu/enterprise/policies/innovation/policy/regional-innovation/

Netherlands and the UK are in the second category (innovation followers), while the third (moderate innovators) contains regions from the Czech Republic, Greece, Spain, Hungary, Italy, Portugal, Slovakia and Poland.

The degree of urbanisation of the regions is measured using Eurostat data on the share of households per region that lives in densely populated or urbanised areas, intermediate urbanised areas, and thinly-populated or rural areas. Table 5.1 gives an overview of the data sources used by indicator.

**Table 5.1 Variables and data sources used in Chapter 5**

| | Sources | Sector coverage, description |
|---|---|---|
| Main variables | | |
| Employment | Cambridge Econometrics | Total economy level |
| Related Variety - Production | BvD (Amadeus), Eurostat (SBS) | Computed for 29 2-digit NACE sectors |
| Unrelated Variety - Production | BvD (Amadeus), Eurostat (SBS) | Computed for 29 2-digit NACE sectors |
| Related Variety - Knowledge | OECD REGPAT | Computed for 121 3-digit IPC classes |
| Unrelated Variety - Knowledge | OECD REGPAT | Computed for 121 3-digit IPC classes |
| Product Sophistication | BvD (Amadeus), Eurostat (SBS) | Computed for 29 2-digit NACE sectors |
| Control variables | | |
| Specialisation | BvD (AMADEUS), Eurostat (SBS) | Computed for 29 2-digit NACE sectors |
| Population Density | Eurostat Regional Data | Total population over land area |
| Compensation per Hour Worked | Cambridge Econometrics | Total economy level |
| Investment per Person Employed | Cambridge Econometrics | Total economy level |
| Manufacturing Employment Share | Cambridge Econometrics | Share of total employment |
| Regional heterogeneity | | |
| Distance to the technological frontier | Regional Innovation Scoreboard | Takes on values 0 (at frontier) to 3 |
| Degree of urbanisation | Eurostat | Share of households in densely, intermediate or thinly populated areas |

*Regional sample:*

The analysis in this chapter covers 250 NUTS2 regions from the EU-28 except Croatia, Cyprus, Malta and Luxembourg. Several islands and remote regions are excluded, for example the Spanish, French and Portuguese overseas regions and islands in the Atlantic and Indian Oceans. Furthermore, a small number of regions is dropped because their boundaries were changed between the 2006 and 2010 versions of the NUTS classification that are used by Cambridge Econometrics and Eurostat respectively.[56] This concerns two Italian and two British regions. Table 5.2 provides summary statistics on all indicators for the estimation sample.

The descriptive statistics indicate that unrelated variety in terms of regional production structures has a higher mean and lower variance across the regions than related variety. The theoretical minimum of both measures is zero, and the theoretical maxima in the dataset employed here are 4.86 for unrelated and 4.64 for related variety. Regarding variety in knowledge generation as measured by patenting activities, related variety has a lower mean as well as variance. The theoretical minimum related and unrelated knowledge variety is again zero, which is indeed attained in the sample. The theoretical maxima are 6.92 for unrelated and 7.71 for related knowledge variety.

[56] See http://ec.europa.eu/eurostat/web/nuts/history for an overview of these changes.

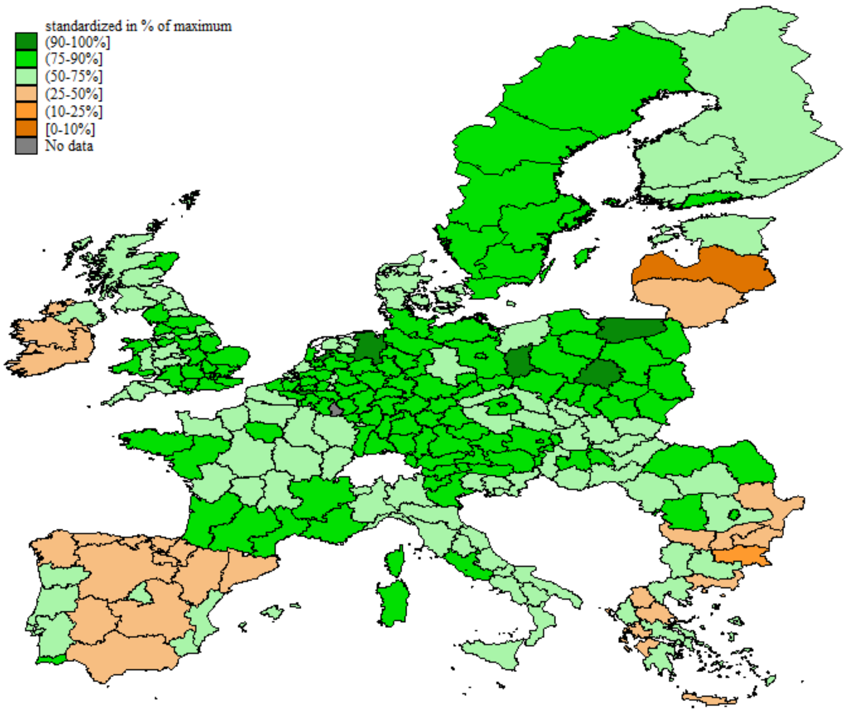
| Table 5.2 Summary statistics – Data used in Chapter 5, 2008-2011 | | | | | |
|---|---|---|---|---|---|
| | Observations | Mean | Std. Dev. | Min | Max |
| Employment Growth | 750 | -0.008 | 0.022 | -0.141 | 0.067 |
| Related Variety - Production | 1000 | 1.890 | 0.422 | 0.331 | 2.728 |
| Unrelated Variety - Production | 1000 | 3.847 | 0.333 | 1.593 | 4.390 |
| Related Variety - Knowledge | 957 | 1.625 | 0.975 | 0 | 4.437 |
| Unrelated Variety - Knowledge | 957 | 3.779 | 1.360 | 0 | 5.744 |
| Product Sophistication | 1000 | 0.024 | 0.316 | -2.351 | 0.622 |
| Specialisation | 1000 | 0.919 | 0.525 | 0.350 | 4.042 |
| Population Density | 1000 | 0.357 | 0.902 | 0.003 | 9.752 |
| Compensation per Hour Worked | 1000 | 14.93 | 7.731 | 1.083 | 37.52 |
| Investment per Person Employed | 1000 | 9.845 | 4.818 | 0.499 | 36.74 |
| Manufacturing Employment Share | 1000 | 0.165 | 0.069 | 0.018 | 0.383 |

*Source: WIFO calculations. Cambridge Econometrics, BvD (Amadeus), Eurostat (SBS and Regional Statistics)*

### 5.2.1. Regional employment growth

Figure 5.1 maps the average annual growth rate of regional employment during 2008 to 2011 for the NUTS2 regions in the sample. Over this period, employment in several countries suffered as a result of the financial and economic crisis that began in late 2008. Latvia registered the largest annual decline, at an average of 8.8% per year, followed by South-Eastern Bulgaria and Galicia in Spain. In general, the Baltic countries, Bulgaria, Spain, Ireland and Greece experienced the largest annual employment contractions. On the other hand, the Polish regions Lodz and Lubusz achieved the highest growth rates, at above 2% per year. Regions from Northern Germany, Belgium and the Netherlands also grew comparatively fast over the period. Many capital regions did better than the rest of their countries, including London, Paris, Madrid, Berlin and Prague.

**Figure 5.1 Regional employment growth, annual average 2008-2011**




*Note: Values standardised between 0 (min.) and 1 (max. in sample)*
*Source: WIFO calculations. Cambridge Econometrics*

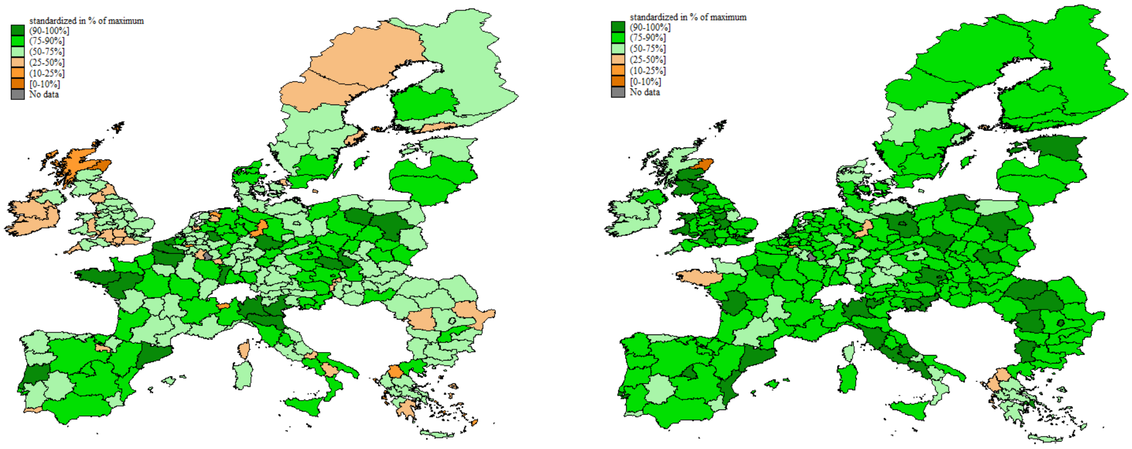
### 5.2.2. Regional related and unrelated variety in production

Figure 5.2 depicts the distribution of related and unrelated variety in production across the NUTS2 regions of the EU. The regions that score highest on related variety are Lombardy, Emilia-Romagna and Veneto (IT), followed by Bretagne (FR) and Catalonia (ES). For unrelated variety, the maxima are obtained by the Polish regions Lesser Poland and Lower Silesia, followed by Tuscany (IT), Bucharest-Ilfov (RO) and Madrid (ES). At the other end of the spectrum, North Eastern Scotland scores lowest on both related and unrelated variety. This region is home to Aberdeenshire, the centre of the European oil industry, and is therefore highly specialised and represents an outlier. Other regions with both low related and low unrelated variety include Walloon Brabant (BE), the Greek regions South Aegean and Epirus, and Braunschweig (DE). In general, comparing the two panels indicates that a few regions in Italy, Spain and Poland score highly on both related and unrelated variety, while in the UK for instance, there is more unrelated than related variety in most regions. Regions in the Central and Eastern European Member States also tend to score highly on unrelated variety. This may be a result of structural change in recent decades going along with new firm formation and FDI inflows introducing new economic activity and knowledge in fields that are less related to existing local production structures (see also chapters 2 and 4).

Figure 5.2 suggests that there is less variation in the distribution of unrelated than of related production variety across the European regions. In addition, the mean value of unrelated variety is higher than that of related variety (see Table 5.2). Hence, employment is more equally distributed across 2-digit NACE sectors in the European regions than within 2-digit sectors (higher mean of unrelated variety) and this holds for a larger part of the regions (lower variance). Put differently, there are more regions that are specialised in 4-digit industries within individual 2-digit sectors than there are regions specialised in entire 2-digit sectors at the expense of others.

**Figure 5.2 Regional related and unrelated variety in production**

**Average related variety, 2008-2011** | **Average unrelated variety, 2008-2011**

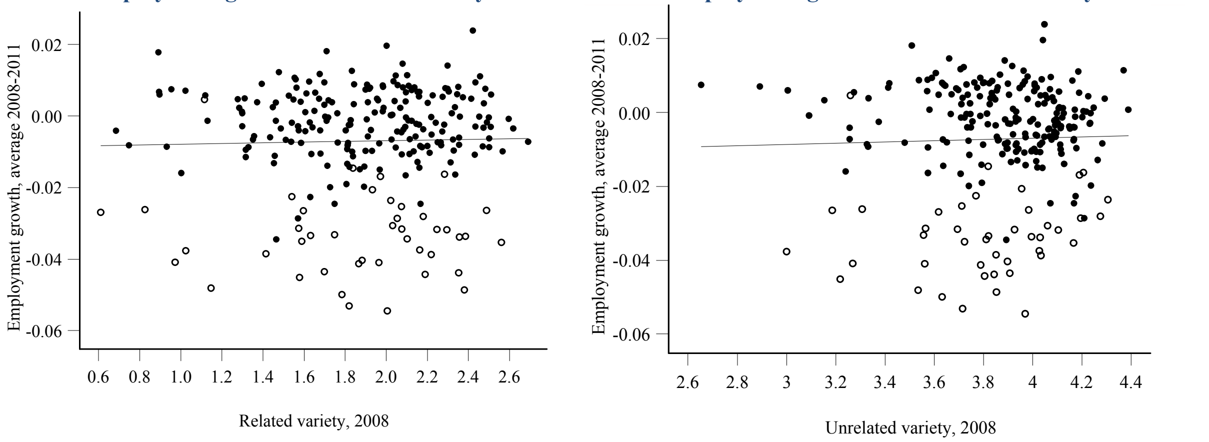



*Note: Values standardised between 0 (min.) and 1 (max. in sample)*
*Source: WIFO calculations. BvD (Amadeus), Eurostat (SBS)*

Figure 5.3 plots average annual employment growth between 2008 and 2011 in the regions against the initial values of related and unrelated variety in production in 2008. Latvia and North Eastern Scotland are excluded because of their strong deviation from the rest of the sample. A weak positive relationship between the variables is visible, but it also emerges that regions belonging to the countries most strongly affected by the crisis (marked with circles rather than dots) may need to be considered separately in the econometric analysis. These countries are Greece, Ireland, Portugal, Spain, Estonia, Latvia, Lithuania and Bulgaria. In most of their regions, employment shrank by more than 2% per year on average.

**Figure 5.3 The relationship between regional employment growth and variety in production**

**Employment growth vs. related variety** | **Employment growth vs. unrelated variety**



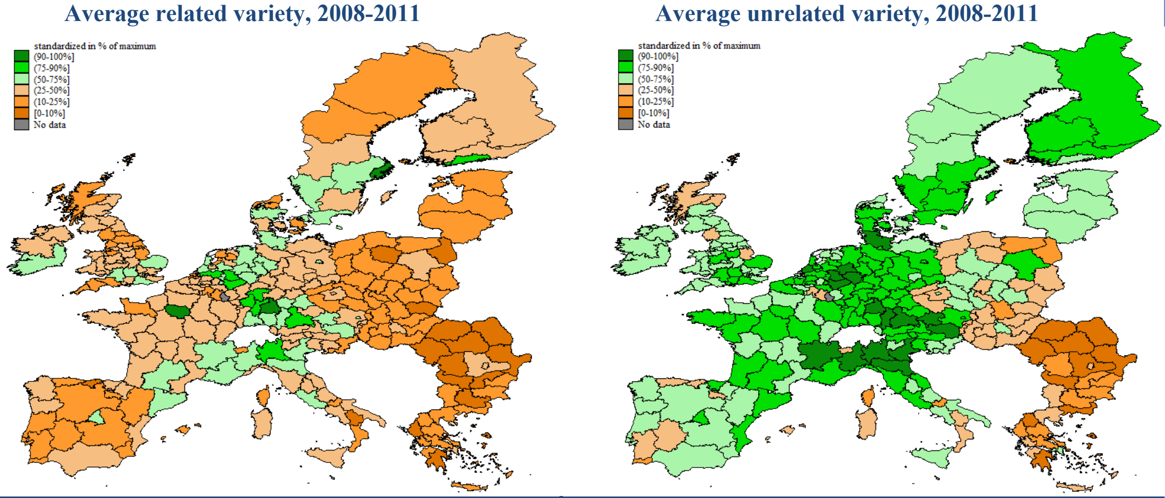

*Source: WIFO calculations. Cambridge Econometrics, BvD (Amadeus), Eurostat (SBS)*

### 5.2.3. Regional related and unrelated knowledge variety

Figure 5.4 maps the distribution of related and unrelated variety in knowledge-generating activities as measured by patenting across the NUTS2 regions. The highest values for related variety can be found in the regions Île-de-France (FR), Stockholm (SE), Stuttgart, Upper Bavaria (DE), and Lombardy (IT). Unrelated variety is highest in Lombardy, Veneto (IT), Upper Austria (AT), Upper Bavaria, and Düsseldorf (DE). Regions from Northern Italy, Western Germany, Austria and Belgium do well on both related and unrelated variety. On the other hand, peripheral regions, especially from Romania, Bulgaria and Greece have low variety of both types. Vest and North-East Romania, Northern Aegean (EL) and North-Western Bulgaria register the minimum values of both measures. On the whole, unrelated variety is higher on average than related variety, suggesting that regional patenting is more equally distributed across 3-digit IPC classes than within them.

**Figure 5.4 Regional related and unrelated knowledge variety**

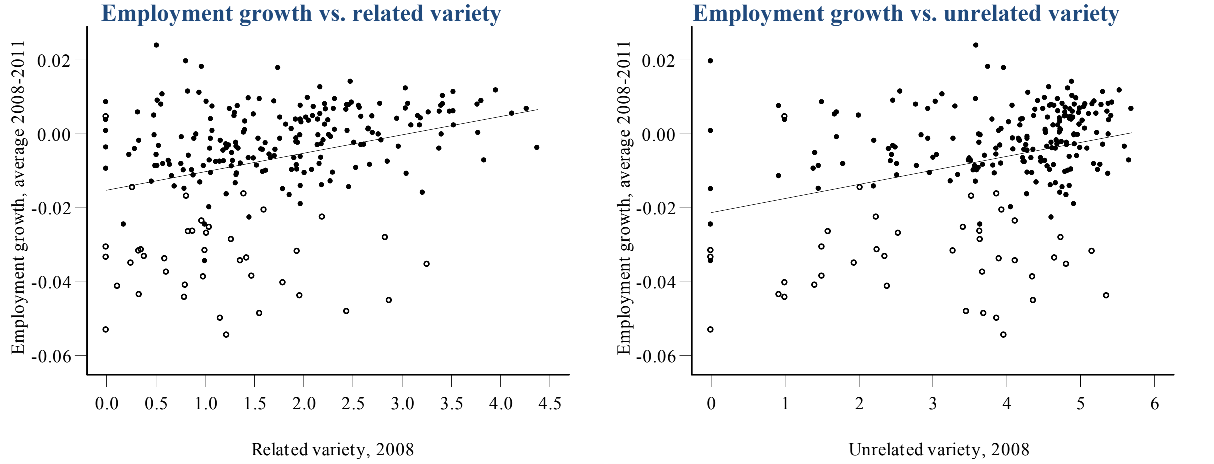
**Average related variety, 2008-2011** | **Average unrelated variety, 2008-2011**




*Note: Values are standardised between 0 (min.) and 1 (max. in sample)*
*Source : WIFO calculations. OECD REGPAT*

Figure 5.5 plots average annual employment growth between 2008 and 2011 in the regions against the initial values of related and unrelated knowledge variety. A positive relationship between the variables is noticeable, as is the tendentially weaker performance of the crisis regions on both measures of knowledge variety.

**Figure 5.5 The relationship between regional employment growth and knowledge variety**

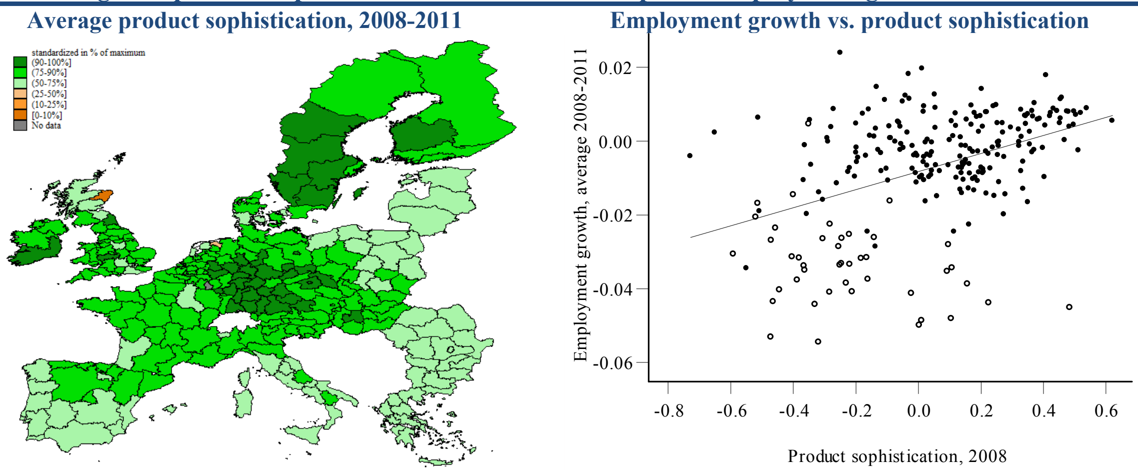



*Source: WIFO calculations. Cambridge Econometrics, OECD REGPAT*

### 5.2.4. Regional product sophistication

The left-hand panel of Figure 5.6 illustrates the distribution of product sophistication across the NUTS2 regions. A core-periphery pattern is visible, with regions in Southern, Western and South-Eastern Germany, but also in Sweden, Finland and Ireland producing the most sophisticated goods. On the other hand, the regions of Romania, Bulgaria, Greece, Portugal and Southern Spain, as well as North Eastern Poland and the Baltic countries score low on product sophistication. North Eastern Scotland is again an outlier, taking on the minimum value in the sample. The right-hand panel of Figure 5.6 indicates a positive relationship between average annual employment growth and initial product sophistication. The regions from the crisis countries clearly lag behind on both measures. The main outliers on product sophistication, Groningen (NL) and Inner London (UK), are excluded from the figure.

**Figure 5.6 Regional product sophistication and its relationship with employment growth**




*Note: Values in left-hand panel are standardised between 0 (min.) and 1 (max. in sample)*
*Source: WIFO calculations. BvD (Amadeus), Eurostat (SBS), Cambridge Econometrics*

## 5.3. The relationship between related and unrelated variety in production and knowledge, product sophistication and economic performance

The main hypotheses tested in this chapter can be formulated as follows:

Hypothesis 1: Related and unrelated variety in production and knowledge are positively related to regional employment growth.

Testing the first hypothesis provides evidence at the aggregate regional level on the impact of related (and unrelated) diversification on economic performance. Therefore, it is the central focus of this chapter. The theoretical mechanism through which related variety, both in production and knowledge generation, contributes to employment growth is through the facilitation of knowledge spillovers between industries or research fields sharing similar technological knowledge. For unrelated variety in production, the mechanism of operation is a portfolio effect, whereby the presence of a variety of unrelated industries insulates regions from negative shocks affecting similar sectors. In addition, unrelated knowledge variety harbours the potential for breakthrough innovations leading to substantial employment effects through the creation of new industries.

Hypothesis 2: Product sophistication is positively associated with regional employment growth.

The second hypothesis builds on the assumption established previously in this study that countries or regions with more sophisticated products in their portfolio have a deeper and broader knowledge base and are therefore expected to perform better in terms of economic growth.

Hypothesis 3: Unrelated variety in production has a stronger positive impact on employment growth in the regions that were most affected by the economic crisis.

The third hypothesis emerges from the descriptive analysis in the previous section, which indicates that the effects of variety on employment growth should be investigated separately for regions from countries that were most heavily affected by the crisis. These regions not only registered lower employment growth between 2008 and 2011 but were also found to lag behind in terms of product sophistication and knowledge variety. They are from Greece, Ireland, Portugal, Spain, Estonia, Latvia, Lithuania and Bulgaria, where employment contracted by more than 2% per year on average. Unrelated variety can be expected to have a stronger positive impact in the crisis regions due to the portfolio effect, whereby a diversity of unrelated industries protects against economic shocks. In general, the special economic circumstances in Europe during the time period considered in this chapter make it likely that unrelated variety plays a larger role than would otherwise be the case.

Hypothesis 4: The effects of related and unrelated variety on employment growth differ by regional characteristics such as their distance to the technological frontier and their degree of urbanisation.

The fourth hypothesis investigates two types of regional differentiation. Firstly, closer to the technological frontier, industries are more mature and therefore at a later stage of their life cycle, so that they benefit more from diversification in related industries. Further from the frontier, unrelated variety could be more growth-enhancing if industries are younger and therefore benefit from diversity. Alternatively, unrelated diversification could be a driver of employment growth in regions closer to the frontier, since these can be expected to possess the cognitive capabilities required to generate growth through the recombination of previously unrelated technologies, creating new goods and industries. Second, the life-cycle view of industrial development also suggests that employment growth in highly urbanised regions benefits from unrelated variety, while in intermediately urbanised regions, related variety should be the main driver.

### 5.3.1. Estimation design

To test these hypotheses, two empirical specifications are estimated using panel data for 250 NUTS2 regions over the period from 2008 to 2011. The baseline equation takes the following form:

Eq. 4: $$\Delta \ln E_{r,t} = \boldsymbol{\alpha} + \boldsymbol{\beta_1} \ln \mathbf{RV_{r,t-1}} + \boldsymbol{\beta_2} \ln \mathbf{UV_{r,t-1}} + \boldsymbol{\beta_3}\mathbf{SOPH_{r,t-1}} + \boldsymbol{\gamma_i}\mathbf{X_{i,r,t-1}} + \boldsymbol{\mu_r} + \boldsymbol{\eta_t} + \boldsymbol{\epsilon_{r,t}},$$

where the dependent variable is annual employment growth in region *r*, $RV_r$ and $UV_r$ denote related and unrelated variety and $SOPH_r$ is regional product sophistication. $X_{i,r}$ contains the control variables for regional specialisation, population density, the regional wage rate, investment per worker and the share of manufacturing employment. All explanatory variables are lagged by one period to reduce endogeneity concerns. Except for product sophistication, which is standardised at a mean of zero and takes on negative values, all variables are included in logarithmic form to ease interpretation. The estimated coefficients on related and unrelated variety can therefore be read as the percentage-point increase in regional employment growth induced by a 1% increase in variety. $\mu_r$ and $\eta_t$ denote region- and time-specific fixed effects, and $\epsilon_{r,t}$ is the usual error term.

Equation Eq. 4 is used to test hypotheses 1, 2 and 3 discussed above. It is estimated to investigate the effects of related and unrelated variety, first in production and then also in knowledge. For both types of variety, separate regimes are then estimated for regions strongly affected by the economic crisis in terms of employment growth and those less affected. This is implemented by interacting all explanatory variables with a dummy variable taking the value 1 for crisis regions and zero for non-crisis regions.

To test hypothesis 4, that is, whether the effects of related and unrelated variety differ by regional characteristics such as distance to the frontier and degree of urbanisation, the following specification is estimated:

Eq. 5: $$\Delta \ln E_{r,t} = \alpha + \beta_1 \ln RV_{r,t-1} + \beta_2 \ln UV_{r,t-1} + \beta_3 SOPH_{r,t-1} + \beta_4 [\ln RV_{r,t-1} \times CHAR_{r,t-1}] + \\ + \beta_5 [\ln UV_{r,t-1} \times CHAR_{r,t-1}] + \beta_6 CHAR_{r,t-1} + \gamma_i X_{i,r,t-1} + \mu_r + \eta_t + \epsilon_{r,t},$$

where $CHAR_r$ stands for regional characteristics and contains either the measure of distance to the frontier taking on (integer) values between 0 and 3, or the variable on the share of households living in densely/intermediate/thinly populated areas per region. This specification is not used to investigate variety in knowledge-generating capabilities since the latter correlates strongly with the measure of distance to the frontier, which is based on an assessment of regional innovation capabilities.

Summarising, the hypotheses formulated in section 5.3 can be re-stated using the estimation equations Eq. 4 and Eq. 5 as in Box 5.4:

**Box 5.4 Hypotheses tested in chapter 5**

Hypothesis 1: Related and unrelated variety in production and knowledge are positively related to employment growth: using equation Eq. 4, this corresponds to $\beta_1 > 0$ and $\beta_2 > 0$.

Hypothesis 2: Product sophistication is positively associated with regional employment growth: using equations Eq. 4 and Eq. 5 this corresponds to $\beta_3 > 0$.

Hypothesis 3: Unrelated variety in production has a stronger positive impact on employment growth in the regions that were most affected by the economic crisis: using equation Eq. 4, this implies that $\beta_2$ is larger in the regime estimated for crisis regions than in that for non-crisis regions.

Hypothesis 4: The effects of related and unrelated variety differ by regional characteristics such as their distance to the technological frontier and their degree of urbanisation: using equation Eq. 5, this implies that the marginal effects of related and unrelated variety on employment growth vary for different realisations of the regional characteristics variable $CHAR_r$.

In both equations Eq. 4 and Eq. 5, additional control variables were considered, including R&D expenditures as a share of regional output and the share of the regional population aged between 25 and 64 that has completed either upper secondary or tertiary education. These variables were not significantly correlated with employment growth in any of the specifications estimated and are therefore not reported.

All equations are estimated using the fixed-effects estimator for panel data in order to account for unobserved variables that can be assumed to remain constant for each region during the sample period. These include region-specific factors such as differences in institutional quality and geographical location. Time-varying effects that affect all regions equally, on the other hand, are controlled for by the time-specific fixed effects.

### 5.3.2. Empirical results

*The impact of related and unrelated variety and product sophistication on employment growth*

The first key result emerging from the econometric analysis is that unrelated variety in production was the dominant driver of aggregate regional employment growth between 2008 and 2011, and that this can largely be explained by its importance in those regions that were most strongly affected by the economic crisis. Given the time period examined, this makes intuitive sense and can be interpreted as evidence in favour of the portfolio effect, that is, the shock-absorbing role of regional diversification into unrelated economic activities. Related variety, on the other hand, has a small positive effect on employment growth only in the non-crisis regions, hinting at the growth-enhancing role of relatedness in regional diversification during more normal economic times. Regarding variety in knowledge-generating capabilities, unrelated variety is also found to matter, although the effect is small and dominated by unrelated production variety for the crisis regions. Thus the results support most of hypothesis 1 - related and unrelated variety in production, and unrelated knowledge variety, are positively related to regional employment growth - while also confirming hypothesis 3, which posits that unrelated production variety has a stronger positive effect on employment growth in those regions that were most affected by the crisis due to the portfolio effect. However, no significant evidence is found regarding hypothesis 2 - that product sophistication is positively associated with regional employment growth. One reason for this could be that product sophistication is persistent over time (see Figure 2.6), so that over the short time period analysed, its effect is captured by the region-specific fixed effects.

Table 5.3 illustrates the findings for related and unrelated variety in production and product sophistication. In the first three columns, the main variables of interest in equation Eq. 4 are added group-wise to examine their effects on employment growth for the full sample of regions. Unrelated variety in production has a statistically significant positive effect that is robust to the inclusion of all control variables considered in equation Eq. 4 (column 3). The estimated coefficient on unrelated variety in column (3) suggests that regions with 1% higher unrelated variety register on average 0.15 percentage points more employment growth per year. To better judge the size of this estimate, equation Eq. 4is re-estimated with the variety variables entering in levels rather than logs (not shown), which yields a coefficient estimate on unrelated variety of 0.05. Using the summary statistics in Table 5.2, this implies that an increase in unrelated variety by one sample standard deviation is associated with an increase in employment growth by 1.7 percentage points, which is a sizeable effect.

When estimating separate regimes for crisis and non-crisis regions by interacting all explanatory variables with a dummy for the crisis countries, it becomes clear that the aggregate effect of unrelated variety in columns (1) to (3) is driven by the importance of this variable in the regions of the crisis countries. The effect of unrelated variety in the latter is more than twice as high as on aggregate (compare column 5 with column 3). A 1% increase in unrelated variety is now associated with a 0.35 percentage point increase in annual employment growth. Alternatively, when estimated with levels of the variety variables, an increase by one standard deviation (in the crisis subsample) goes along with 4 percentage points higher employment growth, which illustrates just how important the portfolio effect seems to be for the crisis regions according to the estimates. In the non-crisis regions, unrelated variety is not significantly different from zero, while related variety has a comparatively small positive effect on employment growth (1 percentage point higher growth for one standard deviation increase in the non-crisis subsample). The results thus provide some evidence of a positive employment effect of diversification into related economic activities, although for the period of analysis, it is outweighed by the importance of a diverse regional portfolio of weakly related industries for absorbing asymmetric shocks affecting particular sectors. The economic crisis that coincides with the time period investigated is therefore likely to play a role in determining the relative magnitude of the impacts of related and unrelated variety on regional employment growth found here.

Regarding product sophistication, no statistically significant effect emerges from Table 5.3. The same holds for almost all included control variables - regional specialisation, population density, investment per worker and the manufacturing employment share - except for the regional wage rate in the non-crisis subsample. Since all these variables are essentially structural indicators, they are unlikely to vary much over the short time period available[57]. Hence a plausible explanation for the insignificance of both product sophistication and the control variables is the difficulty of identifying the effects of variables with little time variation by means of the fixed-effects estimator.

[57] In general, the limitations of estimating the effects on employment growth of structural indicators like investment over a short period of time as is available in this chapter should be highlight. Especially given the crisis-dominated nature of this time period, using the fixed-effects estimator is still the best available option, since it allows to use all available information by controlling for unobservable time-invariant region-specific factors as well as for time-period fixed effects. It also enables to counter endogeneity as far as possible by including lagged values of the explanatory variables.

**Table 5.3 Employment growth and related and unrelated variety in production, Baseline and country regimes, Region level regressions, dependent variable = annual employment growth**

| | NUTS2 regions | | | | |
|---|---|---|---|---|---|
| | Panel Fixed Effects Estimator | | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| **Dependent Variable:** | **Coeff.** | **Coeff.** | **Coeff.** | **Country regimes** | |
| **Annual employment growth** | **(p-value)** | **(p-value)** | **(p-value)** | **Non-crisis** | **Crisis** |
| Lagged ln (related variety) | 0.004 | 0.010 | 0.010 | 0.047 ** | 0.040 |
| | (0.886) | (0.742) | (0.734) | (0.032) | (0.504) |
| Lagged ln (unrelated variety) | 0.169 *** | 0.179 *** | 0.148 *** | -0.032 | 0.352 *** |
| | (0.001) | (0.001) | (0.007) | (0.415) | (0.008) |
| Lagged product sophistication | | -0.019 | -0.019 | -0.005 | -0.025 |
| | | (0.285) | (0.292) | (0.761) | (0.749) |
| Lagged ln (specialisation) | | | -0.012 | -0.001 | -0.013 |
| | | | (0.233) | (0.882) | (0.696) |
| Lagged ln (population density) | | | 0.093 | 0.078 | 0.334 |
| | | | (0.622) | (0.504) | (0.518) |
| Lagged ln (wage rate) | | | 0.035 | 0.038 * | -0.082 |
| | | | (0.139) | (0.052) | (0.470) |
| Lagged ln (investment per worker) | | | 0.008 | 0.015 | 0.015 |
| | | | (0.699) | (0.293) | (0.756) |
| Lagged (manufacturing employment share) | | | -0.228 | -0.148 | -1.257 |
| | | | (0.246) | (0.398) | (0.195) |
| Time Dummies | YES | YES | YES | YES | YES |
| Region Dummies | YES | YES | YES | YES | YES |
| Number of Observations | 750 | 750 | 750 | 750 | 750 |
| Number of Regions | 250 | 250 | 250 | 250 | 250 |
| $R^2$ | 0.295 | 0.298 | 0.312 | 0.366 | 0.366 |

*Note: Robust p-values in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively*
*Source: WIFO calculations*

Table 5.4 presents the results of introducing measures of related and unrelated knowledge variety in addition to variety in production. They provide further evidence of the importance of unrelated variety. For the full sample of regions, unrelated variety in knowledge-generating capabilities has a small but significant positive effect, while unrelated production variety drops in size and turns insignificant. A joint F-test, however, reveals that the two unrelated variety measures are jointly significantly different from zero,[58] indicating that collinearity between them may make it difficult to identify their effects separately. In any case, estimating regimes for crisis and non-crisis countries, a pattern similar to Table 5.3 is found: related variety in production matters in non-crisis regions, while unrelated variety in production has a large and significant positive effect on employment growth in crisis regions. In addition, there is a comparatively small but significant positive effect of unrelated knowledge variety in crisis regions, while related knowledge variety does not matter across all specifications.

Again, the role of the short and crisis-dominated time period analysed in this chapter in driving the effect of unrelated variety should be borne in mind. However, if the results in Table 5.3 and Table 5.4 can be confirmed for a longer time horizon than is available here, they could be read as evidence that diversification in the sense of branching into new and unrelated industrial sectors and fields of technological knowledge is an important driver of regional employment growth on aggregate. While one key finding of chapters 3 and 4 of this study is that in the short run, relatedness facilitates the development of comparative advantage in manufacturing exports, the results in this chapter suggest that at the aggregate economic level, unrelated diversification plays an important role in employment creation. The long-term aggregate employment effects of related diversification, on the other hand, are more likely to be negative, as it represents more industry-specific or intra-sectoral learning effects that tend to raise labour productivity. Overall, both relatedness and diversity are likely to matter for economic performance, although at different levels of aggregation and for different time horizons, and economic policy should take this into account.

58 The p-value of this test equals 0.03.

**Table 5.4 Employment growth and related and unrelated variety in production and knowledge, Baseline and country regimes, Region level regressions, dependent variable = annual employment growth**

| | NUTS2 regions | | | | |
|---|---|---|---|---|---|
| | Panel Fixed Effects Estimator | | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| **Dependent Variable:** | **Coeff.** | **Coeff.** | **Coeff.** | **Country regimes** | |
| **Annual employment growth** | **(p-value)** | **(p-value)** | **(p-value)** | **Non-crisis** | **Crisis** |
| Lagged ln (related variety) | 0.004 | 0.024 | 0.024 | 0.046 ** | 0.041 |
| | (0.886) | (0.447) | (0.440) | (0.049) | (0.742) |
| Lagged ln (unrelated variety) | 0.169 *** | 0.050 | 0.042 | -0.037 | 0.623 *** |
| | (0.001) | (0.475) | (0.557) | (0.360) | (0.003) |
| Lagged ln (related knowledge variety) | | 0.002 | 0.002 | 0.002 | 0.002 |
| | | (0.432) | (0.532) | (0.471) | (0.576) |
| Lagged ln (unrelated knowledge variety) | | 0.012 ** | 0.011 ** | 0.002 | 0.058 *** |
| | | (0.016) | (0.025) | (0.583) | (0.001) |
| Lagged product sophistication | | -0.014 | -0.011 | -0.002 | -0.113 |
| | | (0.413) | (0.562) | (0.899) | (0.321) |
| Lagged ln (specialisation) | | | 0.001 | -0.003 | -0.022 |
| | | | (0.947) | (0.716) | (0.449) |
| Lagged ln (population density) | | | -0.024 | 0.086 | -0.373 |
| | | | (0.894) | (0.480) | (0.365) |
| Lagged ln (wage rate) | | | 0.041 | 0.026 | -0.101 |
| | | | (0.192) | (0.321) | (0.532) |
| Lagged ln (investment per worker) | | | -0.022 | 0.030 * | -0.070 |
| | | | (0.416) | (0.064) | (0.181) |
| Lagged (manufacturing employment share) | | | -0.263 | -0.128 | -0.939 |
| | | | (0.232) | (0.505) | (0.276) |
| Time Dummies | YES | YES | YES | YES | YES |
| Region Dummies | YES | YES | YES | YES | YES |
| Number of Observations | 750 | 677 | 677 | 677 | 677 |
| Number of Regions | 250 | 241 | 241 | 241 | 241 |
| $R^2$ | 0.295 | 0.374 | 0.382 | 0.496 | 0.496 |

*Note: Robust p-values in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively*
*Source: WIFO calculations*

*Regional heterogeneity and the effects of related and unrelated variety on employment growth*

The second main result of the empirical analysis is that distinguishing regions by distance to the technological frontier and degree of urbanisation matters and yields further insights on the effects of related and unrelated variety on employment growth. This provides support for hypothesis 4. Differentiating regions by type further underlines the importance of unrelated variety for regional employment growth that emerged from the analysis above.

When distinguishing regions by distance to the frontier, related variety is found to have a significant positive effect on employment growth for regions at or close to the frontier - that is, for regions belonging to the first two categories of the Regional Innovation Scoreboard, i.e. innovation leaders and followers - but not further away from it. In addition, the growth-enhancing effect of related variety increases with regional proximity to the frontier. Conversely, unrelated variety has a significant positive effect on employment growth for regions furthest away from the frontier or just ahead of the most distant group - that is, for regions belonging to the last two categories of the Regional Innovation Scoreboard, i.e. moderate and modest innovators - but not close to the frontier. The size of this effect is increasing with regional distance to the frontier. These findings suggest that less technologically advanced regions generate employment through diversification into unrelated industries, while for regions at the frontier, diversification into related industries is growth-enhancing. The regions in the top two categories of the Scoreboard are all from the EU-15, which are characterised by relatively mature and technologically advanced industries. The regions in the two bottom categories, on the other hand, are mostly from the Central and Eastern European Member States, which went through a period of highly dynamic structural change (see Figure 3.5) following economic transition in the run-up to EU accession and are characterised by relatively high unrelated variety today (see Figure 5.2).[59] As intermediates suppliers, these

[59] Note that the typology for regional distance to the technological frontier differs enough from that for regions most affected by the crisis to interpret these as separate transmission mechanisms. The correlation between the categorical variables for distance to the frontier and crisis regions is 0.35. Of the crisis countries, the Baltic Member States drop out of the regressions on distance to the frontier because the Regional Innovation Scoreboard 2014 contains no data on them.

countries are also positioned at earlier stages of European and global value chains compared to the EU-15. Therefore, one explanation for the role of unrelated diversification further behind the frontier is the product life-cycle view, i.e. that the industries in the EU-12 are at an earlier stage of development compared to the EU-15 and hence benefit from spillovers from unrelated industries.

When differentiating regions by their degree of urbanisation, the effects differ from what would be expected following the arguments of the product life-cycle view on industrial location. While no significant marginal effects of related variety are found for different levels of urbanisation, unrelated variety is positively associated with employment growth in regions with intermediate and low levels of urban density. This is consistent with the results of Firgo and Mayerhofer (2015), who investigate urbanised versus rural and industrial regions in Austria and find strong positive effects of unrelated variety for the latter group. Especially the intermediate urban and rural regions, which constitute the large majority of regions in Europe, should therefore benefit from diversification into unrelated economic activities.

Table 5.5 shows the estimation results for the differentiation by region types based on equation Eq. 5. The focus is on related and unrelated variety in production rather than knowledge given that stronger effects were found for the former in the previous part of the analysis. For comparison, column (1) reproduces the estimates of equation Eq. 4 in column (3) of Table 5.3 above. From the inclusion of the interaction terms of related and unrelated variety with distance to the frontier (column 2), two conclusions can be drawn. First, regions further behind the frontier registered significantly lower employment growth over the sample period than regions closer to the frontier. Second, regions at the frontier benefit from related variety, while unrelated variety increasingly contributes to employment growth the further behind the frontier a region is. The top panel of Figure 5.7 illustrates how the estimated marginal effects of related and unrelated variety vary with regional distance to the frontier, where the value zero is assigned to regions at the frontier and three to those furthest away.[60] Related variety has the strongest and most significant effect at the frontier. The estimated coefficient in column (2) implies that an increase with related variety by one standard deviation for regions at the frontier is associated with an increase in employment growth by 1.3 percentage points. Unrelated variety has the strongest effect on employment growth for regions furthest behind the frontier. The estimated marginal effect of a one standard-deviation increase in unrelated variety for these regions is a 1.6 percentage point increase in annual employment growth. This is not much larger than that of related variety at the frontier, which follows from the smaller variance of unrelated variety in the subsample of regions that is furthest behind the frontier. It should also be noted that the same set of control variables is included as in the previous tables, but to save space the estimates are not reported. In column (2), both lagged population density and investment per worker are positively associated with employment growth and statistically significant at the 5% level. The size of the coefficients is 0.318 and 0.032 respectively.

Columns (3) to (5) investigate the effects of related and unrelated variety by degree of urbanisation, which is measured by the share of households per region that live in densely populated or urbanised areas, intermediately urbanised areas and thinly-populated or rural areas.[61] Three main conclusions can be drawn. First, densely populated regions registered significantly higher employment growth over the sample period than thinly populated ones. This is consistent with the superior growth performance of capital regions that emerged from the descriptive analysis of EU regional employment growth in section 5.2.1. Second, related variety has no significant effect on employment growth at different levels of urbanisation. Third, the less densely populated a region is, the more unrelated variety contributes to employment growth. This can perhaps best be seen from the bottom panel of Figure 5.7, which shows how the marginal effect of unrelated variety varies with degree of urbanisation. Roughly from the median level of population density onwards, unrelated variety starts having a significant positive relationship with employment growth that reaches its maximum for the least densely populated regions. At the median level of urbanisation, an increase of unrelated variety by one sample standard deviation is associated with approximately 1.6 percentage points higher employment growth. In the sample of European regions considered here, the intermediately urbanised and rural regions have, on average, higher levels of related and lower levels of unrelated variety.[62] Diminishing returns to spillovers from related industries could therefore be a reason why, according to the results, these regions stand to gain the most from diversifying their production structures into unrelated areas.

[60] The graphical representation of the marginal effects of the variables of interest over the range of the interaction variable in this chapter differs from chapters 2 and 4. This is because the earlier chapters estimate nonlinear models, where the marginal effect of the variable of interest depends also on all other explanatory variables (see Box 3.2). This is not the case for the linear models considered here.

[61] In these specifications, the control variable for urbanisation economies, population density on aggregate, is omitted. In most regressions estimated in this chapter, it is not significantly different from zero.

[62] The opposite holds the more densely populated regions are.

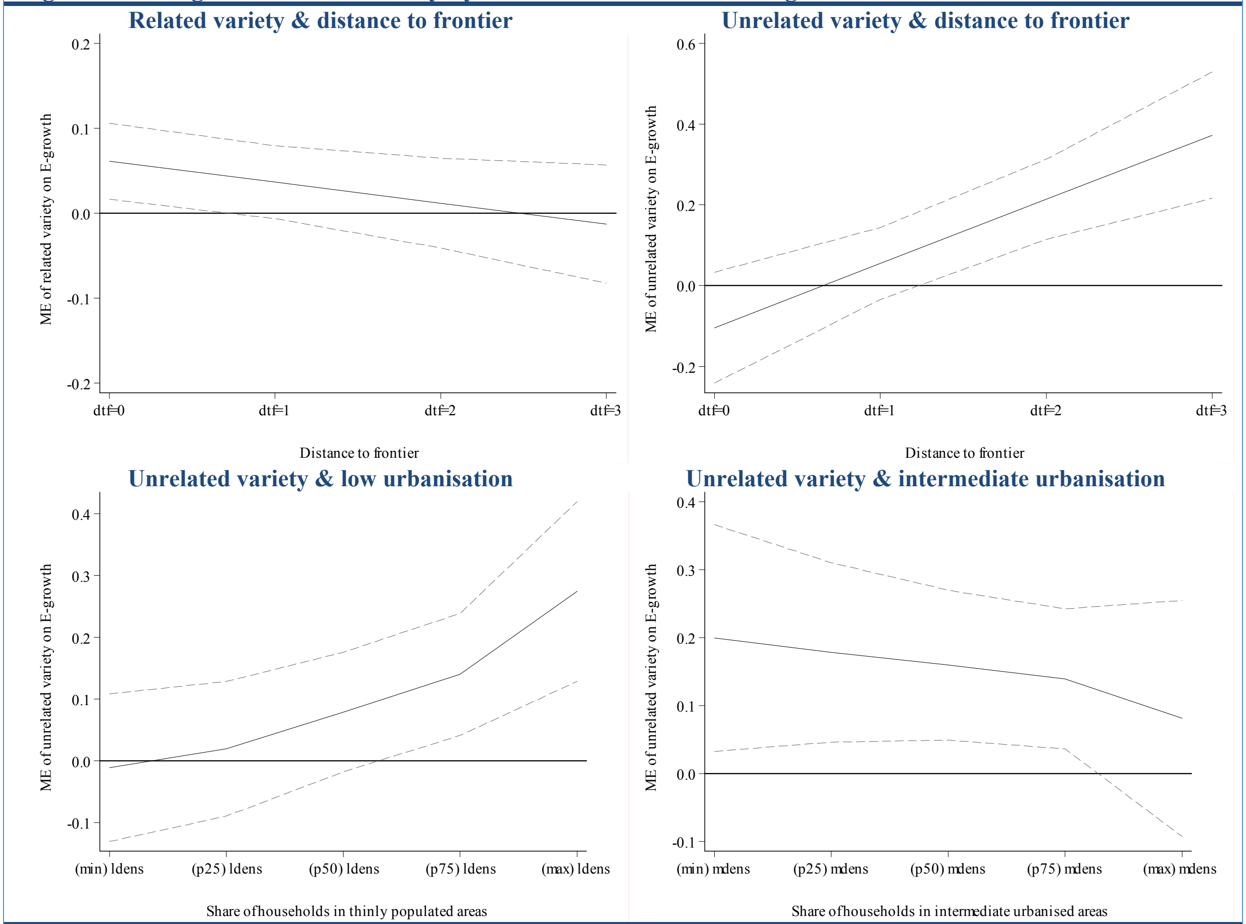
**Table 5.5 Employment growth and related and unrelated variety in production, Region type interactions, Region level regressions, dependent variable = annual employment growth**

| | NUTS2 regions | | | | |
|---|---|---|---|---|---|
| | Panel Fixed Effects Estimator | | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| **Dependent Variable:** | **Coeff.** | **Coeff.** | **Coeff.** | **Coeff.** | **Coeff.** |
| **Annual employment growth** | **(p-value)** | **(p-value)** | **(p-value)** | **(p-value)** | **(p-value)** |
| Lagged ln (related variety) | 0.010 | 0.061 *** | -0.007 | -0.009 | 0.032 |
| | (0.734) | (0.008) | (0.825) | (0.818) | (0.205) |
| Lagged ln (unrelated variety) | 0.148 *** | -0.104 | 0.298 *** | 0.199 ** | -0.012 |
| | (0.007) | (0.137) | (0.000) | (0.020) | (0.851) |
| Interaction related variety x Distance to frontier | | -0.025 ** | | | |
| | | (0.041) | | | |
| Interaction unrelated variety x Distance to frontier | | 0.159 *** | | | |
| | | (0.000) | | | |
| Distance to frontier | | -0.196 *** | | | |
| | | (0.000) | | | |
| Interaction related variety x Densely populated | | | 0.048 | | |
| | | | (0.240) | | |
| Interaction unrelated variety x Densely populated | | | -0.407 *** | | |
| | | | (0.001) | | |
| Densely populated | | | 0.478 *** | | |
| | | | (0.001) | | |
| Interaction related variety x Medium-densely populated | | | | 0.069 | |
| | | | | (0.485) | |
| Interaction unrelated variety x Medium-densely populated | | | | -0.145 | |
| | | | | (0.393) | |
| Medium-densely populated | | | | 0.157 | |
| | | | | (0.470) | |
| Interaction related variety x Thinly populated | | | | | -0.022 |
| | | | | | (0.490) |
| Interaction unrelated variety x Thinly populated | | | | | 0.283 *** |
| | | | | | (0.002) |
| Thinly populated | | | | | -0.364 *** |
| | | | | | (0.002) |
| Other control variables | YES | YES | YES | YES | YES |
| Time Dummies | YES | YES | YES | YES | YES |
| Region Dummies | YES | YES | YES | YES | YES |
| Number of Observations | 750 | 741 | 750 | 750 | 750 |
| Number of Regions | 250 | 247 | 250 | 250 | 250 |
| $R^2$ | 0.312 | 0.387 | 0.330 | 0.315 | 0.331 |

*Note: Robust p-values in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively*
*Source: WIFO calculations*

Overall, the dominant role of unrelated variety as a driver of employment growth for the EU regions remains the most robust feature of the analysis. The results in this section highlight the importance of diversification into unrelated economic activities for regions further behind the technological frontier as well as less densely populated regions. The underlying explanation could be the earlier stage of development of industries behind the frontier and the comparatively high levels of related variety present in intermediate to less urbanised European regions, for which diversification into new industries would thus be a pathway to job creation.

**Figure 5.7 Marginal effects of variety by distance to frontier and degree of urbanisation**




*Source: WIFO calculations. Regional Innovation Scoreboard (2014), Eurostat*

## 5.4. SUMMARY

This chapter has analysed the relationship at the aggregate regional level between employment growth on the one hand and the relatedness of regional production structures and knowledge-generating capabilities as well as regional product sophistication on the other. Its main contribution to this study is to complement the product- and industry-level analyses in the previous chapters by adopting a total-economy perspective. Relatedness in production and knowledge is measured at the aggregate level using recently developed indicators on the distribution of regional employment and patenting activities within the NACE and IPC classifications. Given the availability of regional data on the key variables of interest constructed in chapter 4 of this report, the time period from 2008 to 2011 is considered. Panel data models are estimated that take into account regional differences in terms of the impact of the economic crisis, technological development and degree of urbanisation.

A descriptive analysis of the distribution of related and unrelated variety in terms of sectors of production across the NUTS2 regions indicates that on average, regions register higher values of unrelated than of related variety. This is particularly the case for the regions of the EU-12, where structural change and FDI inflows since economic transition have given rise to less related local production structures. A similar pattern holds for variety in knowledge-generating capabilities.

Summarising the empirical analysis, the most robust result is a significant positive effect of unrelated variety on regional employment growth. This is shown to be particularly strong in those regions where employment suffered most due to the economic crisis in Europe during the time period investigated. Hence this finding can plausibly be interpreted as evidence of the portfolio effect of a diversity of unrelated economic activities protecting regions from the negative employment consequences of asymmetric shocks that are concentrated in particular sectors. Diversification into unrelated industries thus represents an effective strategy for minimising the risk of sudden regional employment contractions and strengthening regional resilience to shocks.

Also regarding knowledge-generating capabilities, a dominant role of unrelated variety for employment growth emerges. Although the effect of unrelated knowledge variety is smaller than that of its production counterpart, this result indicates that the diversification of knowledge-generating capabilities across broad technological fields rather than in narrower related domains contributes to regional economic performance. On the other hand, no significant association is found between product sophistication and employment growth, but due to the high persistence of this indicator established in previous chapters, this is probably attributable to the estimation method employed.

A differentiation of regions by distance to the technological frontier and degree of urbanisation reinforces the importance of unrelated diversification in production structures for regional employment growth. Only for regions at the frontier, related variety makes a significant positive contribution, while the further a region is away from the frontier, the more impact unrelated variety has. Since the regions for which the latter holds are mostly from the EU-12, whereas regions at the frontier are from the EU-15, this evidence is consistent with the life-cycle view on industrial development, whereby more mature industries benefit from related knowledge spillovers, while industries at earlier stages of product development benefit from unrelated spillovers. The recent economic history of the regions from Central and Eastern Europe - characterised by highly dynamic structural change, FDI inflows and integration into intermediate stages of European and global value chains - offers some intuition for this result.

Unrelated variety also benefits regions at intermediate and low levels of urban density, while no effect is found for urbanised regions. A priori, this does not support the product-life cycle view of industry location, i.e. that employment in densely populated urban areas grows through the spillovers that the (unrelated) variety of their sector structure generates for industries at early stages of product development. More peripheral and less densely populated areas provide optimal conditions for industries at later stages that prefer access to industry-specific know-how or related variety. For the sample considered, intermediate- and thinly populated regions are indeed characterised by more related and less unrelated production variety. Thus the results favour an interpretation à la Saviotti and Frenken (2008), whereby growth through diversification into related sectors eventually faces diminishing returns that can ultimately only be offset by diversification into entirely new areas.

Because the time period analysed in this chapter coincides with the recent economic crisis, it is well-suited to identifying the shock-absorbing role of unrelated diversification for employment growth in the short term, and the findings presented here should be interpreted with this in mind. In particular, a stronger impact of unrelated variety on employment growth is to be expected, following the portfolio argument, than would be the case in calmer economic times. The small but positive and statistically significant effect of related variety for the non-crisis regions is an indication of this.

In the long term, unrelated diversification in the sense of branching into new and unrelated industrial sectors and recombining diverse fields of technological knowledge is a key driver of aggregate economic growth. If the results in this chapter can be extrapolated to a longer time period than is available here, they would be consistent with the findings from chapters 3 and 4 that although relatedness may help gain product and industry market shares in the short run, in the long run it can lead to structural lock-in, and it is diversification into less related areas that drives economies forward (Saviotti and Frenken 2008).

On the whole therefore, one conclusion that can be drawn from this chapter is that both relatedness and diversity matter for economic performance - at different levels of aggregation and for different time horizons - and it is important for economic policy to strike the right balance between them.

# Chapter 6.

## SUMMARY OF THE MAIN RESULTS AND POLICY CONCLUSIONS

Smart Specialisation Strategies (3S) have become the primary policy prioritisation logic in recent efforts by the European Union to promote the economic development and growth of European regions. They are an essential element in important domains of EU policy-making, such as EU Cohesion Policy, and have been emphasised in a number of initiatives, such as the Flagship Initiative *Innovation Union* (European Commission 2010a), the Flagship Initiative for a Resource Efficient Europe (European Commission 2011a), or the New Industrial Policy agenda recently put forward by the EC (European Commission 2012a). Over the past years, Smart Specialisation Strategies (3S) have therefore evolved into a key policy approach for achieving the goals set out in its *Europe 2020 strategy* (European Commission 2010c). They are seen as a means to promote Europe's competitiveness, both at the national and regional level, through the development of unique specialisations and the exploitation of diversification potentials. The ultimate goal is to close the productivity gap relative to the US, and maintain or even increase the distance to other emerging industrial nations, as well as support ecologically and socially sustainable development in Europe.

Smart Specialisation Strategies target the capacity of a country or region to develop new economic activities and generate growth-enhancing structural change. The central idea is to promote the diversification around a core set of activities and themes which draw on the existing local knowledge base, with the aim to develop it further by deepening and broadening it (McCann and Ortega-Argilés, 2013). Smart Specialisation Strategies put in place a process whereby diversification into new (and related) economic activities is facilitated thanks to targeted public R&D support. This support fosters entrepreneurial search and discovery in promising new activities, which can benefit from local capabilities and knowledge spillovers, while at the same time broadening the local knowledge base. As such, this approach is distinct from classical specialisation policies, such as early cluster approaches, which typically support existing areas of strength and encourage sectoral specialisation, thus narrowing down the variety of economic activity.

The novelty of the Smart Specialisation approach to industrial and regional policy is that it does away with horizontal approaches to industrial and regional policy that have proven ineffective in the past, and puts the local development context at the focus of policy-making. Smart Specialisation explicitly recognises that economic development at both the national and regional level is highly dependent on specific local capabilities that have accumulated over time and that heavily depend on and co-evolve with untraded technological interdependencies and information flows, common infrastructures as well as economic, technical or educational institutions. This implies that there is no one-size-fits-all solution to promote economic development and structural change in EU Member States and their regions. It is necessary to take into account the heterogeneity of countries and regions in the development and design of industrial and regional policies. For this to be effective, Smart Specialisation policies require a careful analysis of regional or national specialisation patterns and the underlying knowledge capabilities, research competencies and industry structures.

The specialisation patterns of countries and regions follow historic pathways that have evolved in the interplay between a broad set of different local competencies and skills, investments in tangible and intangible assets, and supporting infrastructure. This build-up of specific competencies is both a source of competitive advantage and a source of structural stickiness. It creates unique specialisations and thereby contributes to the emergence of comparative advantages, but many of the associated investments are sticky or even irreversible due to their complementarity with respect to the local knowledge base, and are thus associated with high sunk costs. The presence of high sunk costs in turn reinforces established trajectories of development. Hence, overcoming unfavourable specialisation patterns is difficult in the short run as well as the medium run.

This trade-off represents the principal challenge to Smart Specialisation polices. On the one hand, they have to promote diversification processes into technologically related economic activities. This ensures that the companies that engage in this (local) technological search process can benefit from local capabilities and knowledge spillovers and other untraded interdependencies in the economy. This has a positive impact on their competitiveness and in the case of newly established firms increases the probability of survival. However, if the new and old activities are too similar, i.e. when diversification only happens in technological fields that closely overlap, learning effects will be minimal, the diversity of the knowledge base will not increase and endogenous structural change is unlikely. If on the other hand, Smart Specialisation policies promote diversification into only weakly related economic activities, this will increase the variety of knowledge in the economy, but the activities will only be weakly embedded in the economy, and in the extreme case of totally incongruent knowledge bases neither benefit from nor contribute to the local knowledge base. Solving this trade-off between high proximity or relatedness of knowledge on the one hand, and more diversified, unrelated knowledge on the other, is the key to what makes specialisation policies smart. However, little is known about the "optimum" degree of relatedness across economic activities in an economy.[63]

It has been argued however, that technological search activities of companies are typically narrow in the sense that they have few incentives to engage in research into the discovery of new opportunities beyond (but related to) their core competencies and activities. This has led Rodrik (2004) to conclude that "diversification is unlikely to happen without government action", the reason being that firms typically focus their economic activities and research and innovation efforts around their main fields of activity, reinforcing existing specialisation patterns. Hence, while much has been written about absorptive capacities (cf. Rosenberg 1990; Cohen and Levinthal 1989) and the development of dynamic capabilities (Eisenhardt and Martin 2000; Teece, Pisano and Shuen 1997), such strategies are the exception rather than the norm. For this reason, specialisation and relatedness of economic activities in an economy are likely to be too narrow. If policy does not act to increase the variety of economic and knowledge-generating activities, this may lead to structural traps of development, i.e. specialisations that at some point in time come under competitive pressure, but that are difficult to leave due to change. Hence, there is market failure that justifies policy intervention, as companies do not generally have incentives to engage in the diversification of their knowledge base and their technological capabilities. These can be enforced by systemic failures if the national innovation systems do not properly support the creation of variety.

From a policy point of view it is therefore an important question how to widen specialisation patterns and ensure that comparative advantages can also be achieved in products and industries that draw on knowledge bases which are technologically distant but still related to the established fields of strength of a country or a region. In general, the proponents of Smart Specialisation make a case for targeted R&D support (Foray, David and Hall 2011; Foray and Goenaga 2013). However, one could argue that any measure that increases the variety of economic activities and knowledge in an economy could potentially contribute to the goals of Smart Specialisation, if these ensure that carriers of new capabilities (firms, individuals) are properly embedded in the web of national economic and knowledge-creating activities.

This report has analysed the development of new industrial specialisations and the process of export diversification both at the country level and the regional level for the EU Member States over time. It examined the causes for the observed persistence and patterns of specialisation across countries and industries and technological fields. It has then analysed how education, innovation and FDI at both the national and regional levels can contribute to diversification and hence increase the variety of economic activity in terms of the diversification of export portfolios and industrial specialisations. Finally, it has also studied the impact of different types of diversification patterns on regional employment growth.

**Key empirical findings – Persistence of specialisation patterns in the EU**

- Industrial structures and patterns of comparative advantage of EU Member States are highly persistent over time.
- In the past decade, the EU-13 countries have experienced a more dynamic structural change of their export portfolios than the EU-15 countries.

Empirical evidence presented in this report shows that industrial structures and related patterns of comparative advantages in trade are highly persistent over time across the EU-28 countries, even though a more dynamic development can be observed in the EU-13 countries over the past decade. This evidence holds for highly disaggregated product classes as much as for entire sectors. Econometric analyses presented in this report indicate that this persistence is to a considerable extent due to local technological capabilities that have accumulated over time and country-specific untraded interdependencies such as knowledge spillovers between different domains of the domestic knowledge base.

[63] An optimum degree of relatedness would at the same time maximise knowledge diffusion and achieve variety of economic activities such that the resulting diversity in the economy creates the conditions for further selfsustained expansion by fostering the creation of new economic niches (cf. Hanel, Kauffman and Thurner 2007; Kauffman, Thurner and Hanel 2008).

**Key empirical findings – Relatedness and specialisation patterns**

- Comparative advantages are largely determined by country-specific technological capabilities that have accumulated over time and knowledge flows across technologically related industries.
- Comparative advantages in a country tend to cluster in interrelated industries, and these clusters of industries with comparative advantage themselves cluster in specific country groups.
- New comparative advantages are likely to emerge in economic fields that are related to existing areas of strength, …
- … but high degrees of relatedness also potentially evoke sluggishness in economic structures limiting structural adjustments.

In line with these findings the chapter also provides evidence that new comparative advantages in trade and export potentials are likely to emerge in activities that are related to existing areas of strength. The likely reason for this observation is that these activities can benefit from and are potentially also a manifestation of local externalities – if, for instance, the transmission channel consists of company spin-offs that rely on a well-established knowledge base inherited from their parent companies. Comparative advantages in a country therefore tend to cluster in interrelated industries, as an analysis of specialization patterns across the EU-28 countries shows. Furthermore, these clusters of interrelated industries also cluster in specific groups of countries in the EU-28. Hence, this first set of results provides evidence supporting the view that the specialisation patterns and competitive strengths of a country or a region show properties of path dependent processes, insofar as positive feedbacks between knowledge-generating and knowledge-using activities across specific industries and technologies exist that mutually strengthen the local knowledge base over time, beget new feedbacks and thus ensure sustained international competitiveness in the related economic and technological activities. This evidence also supports arguments in favour of public intervention to boost diversification processes, as it indicates that the underlying technological search is fairly close to existing core-capabilities of the business sector of an economy.

**Key empirical findings – Product sophistication and specialisation patterns**

- Specialising in a product is more difficult for more sophisticated products.
- The EU and its on average more advanced industrialised Member States are more likely to specialise in more sophisticated products.
- The closer countries are to the technological frontier, the more competitive and specialised they are in more sophisticated products.

Diversification happens in two dimensions. On the one hand, it is a horizontal process that affects the patterns of comparative advantages across industries in a country. On the other hand, it is a vertical process that changes the composition of the product portfolio of industries from less towards more sophisticated products. This is a particular variation of technological upgrading. The results presented in this report show that it is more difficult to diversify into more sophisticated products. More sophisticated products involve more complex activities and therefore a larger number of technological competencies to draw upon. While this is a well known outcome, it clearly shows that there are limits to diversification for a given level of technological capability in a country. Indeed, countries that are closer to the technological frontier are typically also more competitive and specialised in more sophisticated products. Building up the capabilities to develop and produce such products depends heavily upon a combination of protracted government investment in the knowledge base of a country or region, and business allocation of resources to innovative investment strategies. This explains why clusters of technology intensive industries can be observed in groups of countries that have developed a broad knowledge base in these industrial activities.

The collective and cumulative character of learning processes therefore makes it difficult for regions or countries that are farther off the technological frontier to succeed in attempts to diversify into industries requiring complex technological capabilities. Rather, the results suggest that they have to pursue the strategy to diversify into more sophisticated products in established industries, and move into more complex activities gradually as they accumulate technological capabilities over time, as suggested by Sutton and Trefler (2011). Leapfrogging from productive structures with low levels of technological sophistication into productive structures with high levels of sophistication is therefore unlikely without sustained investments into education, knowledge absorption and knowledge creation. It is all the more difficult for activities in technological fields where tacit knowledge plays an important role.

| Key empirical findings – Specialisation patterns and economic performance |
| --- |
| • Diversification processes into related economic activities and into unrelated economic activities both matter for economic performance at the regional level.<br>• Diversification processes into related economic activities support the deepening of the regional or national knowledge base of an industry and foster the competitiveness of industries.<br>• Advanced regions benefit from diversification processes into related economic activities, as this tends to increase knowledge spillovers between economic activities. As a consequence, employment growth in these regions is also driven more by diversification into related rather than unrelated economic activities.<br>In regions farther away from the frontier, diversification processes into unrelated economic activities are more important for employment growth.<br>• Unrelated economic activities increase the resilience of regions to business cycle shocks. |

The results presented and discussed so far have illustrated the collective, cumulative and path dependent character of the development of comparative advantages and competitiveness in trade and industrial specialisation more generally across the EU-28 countries. It was argued that, in order to overcome narrow specialization paths, the challenge for Smart Specialisation Strategies promoting research and innovation is to strike the right balance between supporting diversification into related and unrelated technological activities. The importance of this trade-off also emerges from the analysis of the impact of diversification into related and unrelated activities on employment growth across European regions. The results show that while both types of diversification processes matter for employment growth, their importance differs, depending on the regions' characteristics. Relatedness in economic activities is more important for employment growth in the most advanced regions, while regions further away from the technological frontier benefit most from unrelated variety. This shows that industrial regions close to the technological frontier benefit from a deepening of the knowledge base, because their competitive advantage is on average determined by more sophisticated technologies and products. Less developed regions instead benefit from any kind of industrial activity and typically have a weakly developed industrial base, and hence any kind of new economic activities established in the region contributes to the creation of employment. Finally, the results also show that unrelated economic activities reduce the negative impact of external shocks due to a portfolio effect: as unrelated activities are not at all or only weakly linked through untraded interdependencies, cyclical variations do not propagate as easily as when economic activities are related. Hence, a higher degree of unrelated diversity in economic activities supports the resilience of regions to business cycles in terms of employment losses. These results therefore highlight that the debate on Smart Specialisation Strategies should not gravitate around the question of whether diversification needs to be in related or unrelated activities. Rather, they should try to find answers for how to achieve a degree of relatedness that balances all the benefits and downsides associated with the extreme poles of potential diversification patterns. Furthermore, given the high heterogeneity of development patterns across regions, it will vary considerably.

Another important aspect of Smart Specialisation Strategies concerns potential leverages of Smart Specialisation policies. While targeted R&D support is one important instrument often referred to in policy debates on Smart Specialisation, the potential measures to build up capabilities to foster diversification are manifold, since a broad range of players is involved in the processes that determine specialisation patterns. Local firms, international suppliers and customers, service providers, researchers, entrepreneurs etc., all of these have an impact on which fields a country or region is specialised in and potentially act as catalysts for driving structural change (McCann and Ortega-Argilés 2013). One important lever that has been examined in this report is education.

| Key empirical findings – Education, skills and specialisation patterns |
| --- |
| • Knowledge capabilities favour gaining world market shares and the development of new, as well as a deepening of existing, specialisations.<br>• Countries with higher average levels of educational attainment are more specialised in high-end niche markets. Especially in tertiary education, higher levels reduce difficulties in specialising in more sophisticated products.<br>• Higher levels of educational attainment help countries tap into new industries and gain world market shares in products that are technologically more distant to the core competencies of the business sector of an economy. |

The results show that educational investments play an important role in breaking up narrow specialisation patterns. The report shows that educational attainment in tertiary education in particular favours gaining world market shares in trade and the development of new specialisations or the deepening of existing ones, also in products that are technologically more distant to the core-competencies of the business sector of an economy. It furthermore favours specialisation in high-end niche markets, as higher levels of educational attainment also reduce difficulties in specialising in more sophisticated products. The educational system therefore plays a key role in diversification processes and should therefore be a constitutive element of Smart Specialisation policies.

Measures to enhance education attainment and skill levels are key for improving the local skills base. Nevertheless, one has to consider that firms also contribute to the enhancement of the local (regional or national) knowledge base through innovation activities, learning-by-doing, on-the-job training, improved company routines or technological blueprints. Existing productive structures are therefore an important element for building up local skills and the knowledge base. Educational systems should therefore not only be linked to the labour demand of firms located in a region, but also adapt flexibly to their changing requirements over time. Education policies and measures for improving job prospects for youth (cf. European Commission 2010b) should therefore not only contribute to the accumulation of local capabilities, but also strive to better match skill profiles (i.e. labour supply) to the (future) demand for skills. This would also allow providing a clearer picture of job opportunities for young people, one of the goals identified in the “Youth on the Move” initiative (European Commission 2010b).

Nevertheless, the trade-off between perfect relatedness and perfect diversity that characterised Smart Specialisation Policies in general carries over to educational policies, because if educational activities are too focused on the needs of the business sectors, i.e. if the links between the business and the educational sector are too tight, too little new knowledge from other domains will flow into the system, with the effect that the variance of knowledge and skills levels among economic activities becomes too small which can reinforce structural traps (cf. Cowan and Jonard 2004). Smart Specialisation policies therefore have to solve the trade-off between providing highly specialised skills and high-quality general education (incl. interdisciplinary approaches). For instance, in the context of tertiary education it is important to strike the balance between developing and supporting a system of advanced technical colleges linking up their educational and research agendas to business needs, especially in a regional context and supporting general universities that should provide high-level general education by linking up to leading edge science. This balance will also depend – as has been discussed before – on the general level of technological capabilities of a country or region and its distance to the technological frontier.

While the empirical evidence established in this report suggests that similar mechanisms are in place at both the national and regional level, policy measures should take into account that regions are far more open than countries causing externalities and interdependency issues. For instance, training programmes might cause mismatches between the skills available in the workforce and those required by local firms if they are not well coordinated. In the worst case, such a programme will cause outward migration of the newly skilled employees if they do not find adequate jobs in the region or country they have been trained in. In this case, any positive effect of skills enhancement programmes might blow off (McCann and Ortega-Argilés 2013)[64].

In addition to investments in human capital, knowledge inflows from abroad are also likely to have an impact on the specialisation patterns and diversification potentials of a country. It is a long-standing belief among policy makers and scholars that inward FDI is one of the most important channels through which foreign technology, management skills and production know-how diffuses in an economy and contributes to domestic long-run growth. However, the existing evidence of the impact of inward FDI on the domestic knowledge base is mixed and the potential impact of inward FDI on the domestic knowledge base is ambiguous. For instance, some authors find that foreign ownership of companies is often a predictor for both reduced local R&D cooperation and reduced in-house R&D (cf. Knell and Shrolec 2005). Other studies in turn argue that this is mostly the case in industries with low technological intensity and that indeed foreign subsidiaries have a higher propensity to innovate when they are active in technology-intensive sectors of the host country (cf. Damijan, Kostevc and Rojec 2010). Furthermore, other results suggest that in the EU-13 countries foreign owned firms not only introduce technological innovation, but also positively affect the innovation performance of domestic firms (European Commission 2012b). Little is known about the impact of inward FDI on comparative and competitive advantages and how it interlinks with the domestic knowledge base. This report has examined these issues.

This set of results presented in this report shows very heterogenous effects of inward FDI on comparative and competitive advantages, as well as industrial specialization patterns at the regional level (see summary in the box above). For instance, higher shares of foreign-owned companies in the manufacturing sector go along with higher average world market shares across economic activities in an economy. However, if the analysis focuses on the impact of the share of foreign-owned companies in a particular industry on competetive advantage (world marks share), then the reverse is true: a high share of foreign-owned companies in an industry is negatively related to its comparative and competitive advantage. This result is nevertheless inconclusive. It could be related to the fact observed in the FDI literature that FDI investment is highest in sectors where the world market is

[64] Another aspect related to the development of domestic knowledge and diversification is the inward labour mobility of highly qualified labour. While this aspect has not been analysed in the present studies, a number of studies suggest that this has a positive impact on the competititveness of countries and contributes to diversification (cf. Zucker, Darby and Torero 2002; Song, Almeida and Wu 2003; Moen 2005; Hunt and Gauthier-Loiselle 2008; Wadhwa et al. 2008; Fallick, Fleischman and Rebitzer 2006; Boschma, Eriksson and Lindgren 2009). The support of labour mobility should therefore be considered an integral part of Smart Specialisation Policies.

typically large. As a consequence, the average world market shares and also the comparative advantages on average will be lower, as it is more difficult to capture large market shares in large markets. At the same time, the result could also indicate that FDI flows towards activities with lower competitiveness by domestic exporters. This example illustrates that, by and large, direct effects of FDI on the comparative and competitive advantages of the host country cannot be established unequivocally in the analytical set-up of this study. However, the analysis of how inward FDI affects the domestic knowledge base in this study has been more revealing.

**Key empirical findings – Foreign direct investments and specialisation patterns**

- A high aggregate share of inward FDI in employment in the manufacturing sector of a country is positively related to competitiveness and comparative advantages in trade, but …
- … at the level of single industries a high share of foreign-owned companies in that industry is negatively related to its comparative and competitive advantage, whereas …
- … for any given share of foreign-owned companies in an industry increases in inward foreign direct investment in that industry have a positive impact on its comparative and competitive advantage.
- When domestic activities are weakly linked to the domestic competence base, changes in inward FDI support the development of comparative and competitive advantages, and therefore support diversification across industries.
- The effect of local capabilities on comparative and competitive advantage across industries is higher in sectors with a higher share of foreign-owned firms.
- The effects of inward FDI depend on the stage of technological development of the host country: The most advanced countries benefit less from a higher share in foreign-owned firms in its manufacturing sector than catching-up countries.
- Industries in less advanced countries tend to specialize in more sophisticated products when the share of foreign-owned companies in the manufacturing sector is high, whereas the reverse is true for the more advanced countries.
- In the most advanced EU Member States for any given share of foreign owned companies in the manufacturing sector changes in FDI have a positive impact on comparative advantages in more sophisticated products. In technologically less advanced countries changes in FDI reinforces comparative advantages in less sophisticated products.

When domestic activities are weakly linked to the domestic competence base, changes in inward FDI have a positive effect on the development of comparative and competitive advantages, and therefore support diversification across industries. However, the effect of local capabilities on comparative and competitive advantage across industries is higher in sectors with a higher share of foreign-owned firms, which indicates on the one hand that FDI tends to flow to sectors that are closely related to the local competence base, and that FDI contributes more to a deepening rather than a broadening the local knowledge base. This is in line with findings on the impact of inward FDI in the EU (European Commission 2012b). Hence, while inward FDI could potentially contribute to diversification, it tends to deepen existing specialisations because foreign owned firms seem to be more interested in exploiting local knowledge and related externalities to their own benefit. For profit maximising companies this is quite a natural strategy to pursue, and recently published research on FDI location at the regional level across the EU countries supports this view (cf. Villaverde and Maza 2015).

Hence, while FDI may potentially hold the promise to broaden the knowledge base of an economy and thus be a suitable instrument in the pursuit of Smart Specialisation, the results presented indicate that this promise may be overrated. Nevertheless, the results indicate that inward FDI can indeed contribute to strengthening existing comparative and competitive advantages. Whether these effects materialise will depend on how well foreign-owned companies can draw on existing local capabilities and hence contribute to their embeddedness in the local productive system (cf. Narula 2011). If countries fail to embed foreign-owned companies that are active in areas that are weakly related to the established production and innovation systems, they are likely to lose these companies again in the medium term. The measures needed to embed foreign-owned companies in the local production and innovation ecology will differ across regions, but generally they should try to support foreign-owned firms in developing complementartities between the companies own capabilities and the supply and generation of local capabilities and production factors.

In addition to investments in human capital and knowledge inflows from abroad, the report has also examined the impact of knowledge generation activities (captured by patenting) on the specialisation patterns and diversification potentials of a country. It has been argued earlier that companies have an incentive to engage in research and innovation activities that are closely related to their core competencies. The report has examined this question with regard to the relatedness of technological search activities and knowledge generation in technological fields that are close to local, i.e. regional, technological capabilities.

**Key empirical findings – Local technological search and knowledge generation and specialisation patterns**

- Industries patenting more in technological fields that are closely related to local technological capabilities are more likely to have developed a comparative advantage.
- If an industry (NACE 4 digit) increases the proximity of its patenting activities to technological fields that are closely related to local technological capabilities (local technological search) this has a positive impact on the comparative advantage of the industry.
- Patenting in technological fields that are closely related to local technological capabilities weakens the positive impact of local technological search on the development of comparative advantages when the industry is already highly embedded in the existing productive structures.
- Local technological search has a stronger impact on the development of comparative advantages in industries producing more sophisticated products.

The results support this view. They show that local technological search and knowledge generation reinforce existing specialisation patterns. Industries that patent in technological fields closely related to the local knowledge base also have comparative advantages relative to other industries where this is not the case. However, the results also suggest that local technological search may eventually weaken comparative advantages if it is too narrowly focused. The results therefore support the case for public intervention through targeted R&D support (Foray, David and Hall 2011; Foray and Goenaga 2013).

The aim of this targeted R&D support should be to promote the renewal of established economic activities as well as innovation and diversification into products or technologies that are related to established competencies. In this way they should support the emergence of new activities that are rooted in the productive system of a country (or region). It should encourage the recombination of established competencies with new ones and ensure that activities of knowledge/technology creation and technology diffusion are well embedded in local productive and innovation systems.[65] The recombination of capabilities can happen through a number of channels. The most important policy options are:

1 Mission-oriented policies,

2 Policies supporting entrepreneurship, discovery and recombinant technical change in industries, and

3 Research and technology policies targeting relatedness and recombination.

These broadly defined fields of action are interdependent and individually have a number of strengths and weaknesses.

Mission-oriented policies that focus on societal challenges may trigger the recombination of competencies across technological fields and sectors. Mission-oriented policies in the context of Smart Specialisation strategies should explicitly take into account local capabilities. This means that new missions should build on these capabilities and aim at achieving the mission’s goals by developing these capabilities further through ambitious technological search and recombination.

One potential danger is that the goals set out by the mission rely too heavily on undeveloped capabilities (e.g. new principles of operation or materials) or on capabilities that are not related to existing capabilities. In this case it is likely that the mission will fail, or that considerable long-term investments and public risk-taking in buildingup capabilities and human capital to accomplish the mission are needed while there is no guarantee that these investments contribute to achieving the mission’s goals. Nevertheless, challenging missions and challenging domains of application of technologies are often important in achieving significant technological breakthroughs.

Mission orientation in the context of Smart Specialisation policies therefore comes with a trade-off that has no easy solution: The policy design has to find the right balance between mission driven diversification relying on related technologies and mission-driven diversification relying on weakly or unrelated technologies. In this regard, one has to take into account that, on the one hand, technological practice often throws up important questions requiring further scientific investigation. On the other hand, scientific research often identifies opportunities from its own results that prime commercial application. Therefore, there is a major reason for being concerned with the diversity of the research and the scientific portfolio, especially in the context of mission orientation.

[65] For extensive discussions on the importance of recombinant technical change see Weitzman (1998), Bresnahan (2012), or Arthur and Polak (2006) or Arthur (2009).

This suggests that in the design of mission oriented programmes it is necessary to define goals broadly, while ensuring bottom up research on related problems, both from a broadly scientific and more narrow technological and engineering perspective. This is all the more important in preventing mission orientation from promoting technological lock-in. It is also necessary for an exchange of findings and problems between these different domains to take place to ensure cross-fertilisation. While this may sound like what is nowadays known as “new” mission-orientation (as we see it for instance in the Horizon 2020 programmes), there is however an important difference. Mission orientation in the context of Smart Specialisation capitalises on existing capabilities and tries to exploit diversification potentials by means of the design of selection mechanisms and the specification of missions.

Other difficulties associated with mission orientation should be considered as well. As Mowery (2009) works out, success in mission-oriented programmes stands or falls with complementary market-making measures. Public procurement policies are important complements to ensure that markets are created for products and technologies for which a-priori no or only very small markets exist. These publicly created market niches have to ensure that learning processes can take place that eventually lead to the technological feasibility and economic viability of the related products and services (cf. Kemp, Schot and Hoogma, 1998). However, such processes may require minimum market sizes and are thus not an option for small countries (unless coordination in larger economic areas like the EU takes place). In addition, they may also lead to rent seeking by large incumbents in the market. Furthermore, additional regulations and specific tax measures may also be needed to ensure that viable markets for these products eventually emerge.

In order to avoid “picking the winners” approaches, a “Smart Specialisation” policy should support entrepreneurship and entrepreneurial discovery (Foray, David and Hall 2011; Foray and Goenaga 2013). The emphasis should lie on innovation activities that aim to recombine competencies across technological fields and sectors. Such processes are typically supported by a number of knowledge transfer mechanisms. These include labour mobility, entrepreneurial activities through spin-offs, and the design of award mechanisms for R&D support programmes.

Labour mobility is an important mechanism for the transfer and recombination of knowledge. For instance with respect to geographical mobility the economic literature has repeatedly stressed that the mobility of highly qualified workers (such as researchers) has a positive impact on the competitiveness of countries, regions and firms. In this respect, a number of studies have found that mobile researchers are an important resource pool, which help to improve national and firm-level R&D performance, as well as integration into international R&D networks and increased entrepreneurial and patenting activity (cf. Zucker et al. 2002; Song et al. 2003; Moen 2005; Hunt and Gauthier-Loiselle 2008). Furthermore, a by now relatively large body of empirical research (cf. Wadhwa et al. 2008; Fallick, Fleischman and Rebitzer 2006) shows that, even within a region, the mobility of researchers between sectors and firms may have a positive impact on competitiveness. Boschma et al. (2009) on the other hand show that employees recruited from related industries increase productivity, whereas new recruits from the same industry have a negative impact on performance. Labour mobility is therefore not only a major source of knowledge spillovers but also a source that can contribute to recombinant technical change.

Of even greater importancethan labour mobility between related industries is the mobility between industry and academia. A recent study has shown that industry researchers often start their careers in the public sector to then change into generally more applied industry research (Huber et al. 2010). The relative majority (42.3%) of the industry researchers surveyed in the cited study describes their career path as one starting in the public sector and ending in the private sector. Hence, this type of mobility fosters knowledge flows and potential recombination between industrial capabilities and related academic knowledge bases. In addition, this type of mobility also supports the cooperation between academia and industry (cf. Cohen, Nelson and Walsh 2002).

To support labour mobility, labour market policies should on the one hand develop measures that not only support job mobility between related industries within a country, but also across EU-28 countries and regions. On the other hand, framework conditions and regulations have to be screened in order to eliminate barriers to labour mobility between industries. Such barriers could be industry-specific labour norms, non-compete clauses in labour contracts or differences in salaries for workers with comparable qualifications caused by industry-specific collective agreements. In order to support mobility between the academic and the industrial sector, cooperative research programmes seem to be an appropriate vehicle. Similarly, public policy should provide incentives and support collaborative research activities between companies in technologically related industries. However, while internationally good examples of such cooperative research programmes exist, it has to be acknowledged that they often suffer from problems related to the overall objectives they pursue, to conflicts between short run and long run goals of the programmes and participating partners, or the repartition of IPRs between the involved partners. Hence, the potential of such measures to support Smart Specialisation policies should be re-examined in greater detail in dedicated studies.[66]

Spinoffs can also significantly contribute to industrial restructuring and related diversification processes. While entrepreneurship policies are widespread across countries and most likely to be overrated (cf. Nightingale and Coad 2013, 2014), the support of employee start-ups and spinoffs should be an integral part of Smart Specialisation policies. Klepper (2001) argues that spinoffs inherit routines (and thereby specific capabilities) from their parent companies. While these transplanted routines will perform a subset of functions performed in the parent, spinoffs will however combine them with other different routines. Both the performance and output of the spinoffs will therefore depart from their parents. As Klepper explains, this is also the reason why such firms also have a higher probability of survival than other types of start-ups. This is related to the experience their founders have accumulated in related industries (Klepper 2007).

Viewed from a micro perspective, the processes Klepper (2001) describes are the essence of diversification in related fields of economic activity. Therefore, entrepreneurship policies should focus on or give priority to the support of employee start-ups in the context of Smart Specialisation strategies. The downside of this approach is, of course, that the promotion of employee start-ups is not equally possible across industries: generally technology intensive firms will have more routines than firms with low technological intensity because their activities are more complex, and hence, spinouts will be more likely for such types of companies. In industries where the technological intensity is low, the opportunities for employee start-ups may be more limited.

Established research and technology policies could also be modified so that they are better able to target relatedness and recombination. Non-mission oriented bottom-up types of research funding measures and programmes could target related and recombinant technical change more accurately through specifically designed award mechanisms favouring R&D projects targeting recombinant technical change and diversification over incremental technical change. Of course, one should not make the mistake of thinking that peer review processes are able to adequately distinguish between work with the potential for radical innovation and work that promises an incremental advance of existing lines of scientific investigation and technological development. However, peer review processes can be designed to limit incremental technical change (favouring specialisation) and promote recombinant technical change (favouring diversification).

More precisely, the evaluation of research projects could be linked to the four distinct patterns of diversification discussed in Foray, David and Hall (2011).[67] For instance, the intensity of the support of such projects could vary in function of these patterns, as they are likely to imply different risk profiles. Hence, they would also require varying degrees of support intensity. More ambitious types of diversification that are also more risky should receive higher funding than less risky types of diversification. For instance, it is very likely that research projects that imply diversification through transition are technologically less risky than research projects that aim at diversification through re-domaining. Hence, the latter type of projects should typically receive – ceteris paribus – higher funding. While in practice it seems probable that it would be difficult to work out general principles of funding that would be able to fully take diversification processes into account, substantial knowledge on the patterns of technical change nowadays is available and should be used to design research funding. As recombinant technical change is a key ingredient of related diversification knowledge, this type of technical change should be used in the context of Smart Specialisation approaches.

Overall, this discussion of the results of this report and its policy implications underscore that Smart Specialisation policies require a smooth coordination of a larger set of diverse policy measures, which take into account both the local context and all the involved players, rather than a perfect set-up of single policies (McCann and Ortega-Argilés 2013).

[66] In this context it is important to acknowledge that in the past the flows of skilled labour were quite unilateral, flowing from the catching-up to the technologically most advanced countries. This brain drain has especially detrimental effects on regional development potentials. The incentives for the highly skilled are complex (cf. Huber et al. 2010; Unterlass et al. 2013), and in the context of the development of Smart Specialisation Strategies it would be important to also address measures to limit regional brain drain.

[67] The authors distinguish between transition, modernisation, traditional diversification, and radical formation or re-domaining. Transition involves extending the range of application of given engineering and manufacturing capabilities to another, technologically-related domain. It implies a recombination of new types of market-specific knowledge with technological knowledge that is close to technologies a company currently deploys. Modernisation involves the recombination of existing capabilities with general-purpose technologies (GPTs) such as information technology or nanotechnology, thereby boosting productivity and extending the potential range of applications. Traditional diversification involves exploiting economies of scope such as the development of new lines of productive activities for a given technology. It involves the recombination of existing productive knowledge or the exploitation of knowledge commonalities with knowledge about new or different market segments in which companies where previously not active. Radical formation implies the creation of entirely new domains of economic activity by using new domains of knowledge to re-examine and solve productive tasks and technological problems for which significant technological competencies exist in a country or region. Arthur (2009) refers to this process as “redomaining”. For instance, medical imaging devices (e.g. MRI) were developed as insights from nuclear physics were applied to medical problems.

# REFERENCES


Abdon, A., Bacate, M., Felipe, J., Kumar, U. (2010), 'Product Complexity and Economic Development', Levy Economic Institute Bard College Working Paper, N° 616, 2010.

Acemoglu, D., Aghion, P., Zilibotti, F. (2004), 'Distance to frontier, selection, and economic growth', National Bureau of Economic Research Working Paper, N° 9066, 2004.

Achen, C. H. (2005), 'Let's Put Garbage-Can Regressions and Garbage-Can Probits Where They Belong', *Conflict Management and Peace Science*, N° 22(4), pp. 327–339.

Aghion, P., Boustan, L., Hoxby, C., Vandenbussche, J. (2005), 'Exploiting states' mistakes to identify the causal impact of higher education on growth', National Bureau of Economic Research Working Paper, 2005.

Altzinger, W., Maier, G. (1996), Crossborder Development in the Vienna-Bratislava-Region: A Review, Switzerland, European Regional Science Association 36th European Congress ETH Zurich.

Alvarez, R., Görg, H. (2009), 'Multinationals and plant exit: Evidence from Chile', *International Review of Economics & Finance*, N° 18(1), pp. 45–51.

Amador, J., Cabral, S., Maria, J. R. (2011), 'A simple cross-country index of trade specialization', *Open economies review*, N° 22(3), pp. 447–461.

Amison, P., Bailey, D. (2013), 'Industrial diversity and innovation spillovers: dynamic innovation and adoption', WWWforEurope Working Paper, N° 45, 2013.

Antonelli, C. (1998), 'The dynamics of localized technological change. The interaction between factor costs inducement, demand pull and Schumpeterian rivalry', *Economics of Innovation and New Technology*, N° 6(1), pp. 97–120.

Antonelli, C. (2006), 'Localized technological change and factor market: constraints and inducement mechanisms', *Structural Change and Economic Dynamics*, N° 17, pp. 224–247.

Arthur, B. W. (2009), *The Nature of Technology*, New York, Free Press.

Arthur, B. W., Polak, W. (2006), 'The evolution of technology with a simple computer model', *Complexity*, N° 11(5), pp. 23–31.

Atkinson, A. B., Stiglitz, J. E. (1969), 'A new view of technological change', *Economic Journal*, N° 79(4), pp. 573–578.

Auerwald, P., Kauffman, S., Lobo, J., Shell, K. (2000), 'The production recipes approach to modelling technological innovation: an application to learning by doing', *Journal of Economic Dynamics and Control*, N° 24, pp. 389–450.

Baláž, V. (2011), *Regional Innovation Report (Bratislava Region), Regional Innovation Report,* Technopolis Group, UNU-Merit Maastricht University, Fraunhofer ISI.

Barro, R. J., Lee, J. W. (2013), 'A new data set of educational attainment in the world, 1950–2010', *Journal of Development Economics*, N° 104, pp. 184–198.

Bednar, P., Danke, L., Grebenicek, P. (2013), 'Towards Creative Clusters: Mapping and Development of Creative Industries in Slovakia', *Recent Advances in Environmental Science*, Lemesos, WSEAS Press, Cyprus, pp. 260–265.

Benedictis, L. D. (2005), 'Three decades of Italian comparative advantages', *The World Economy*, N° 28(11), pp. 1679–1709.

Böheim, M., Friesenbichler, K. S. (2014), 'Does Accession to the European Union Foster Competition Policy? Country-level Evidence', WIFO Working Paper, N° 491, 2014.

Boschma, R., Capone, G. (2014), *Institutions and the Direction of Industrial Diversification: An Evolutionary Approach to 'Varieties of Capitalism.'.*

Boschma, R., Eriksson, R. H., Lindgren, U. (2009), 'How does labour mobility affect the performance of plants?', *Journal of Economic Geography*, N° 9(2), S. 169–190.

Boschma, R., Frenken, K. (2011), 'Technological relatedness and regional branching', in Bathelt, H., Feldman, M., Kogler, D. F. (eds.), *Beyond Territory: Dynamic Geographies of Innovation and Knowledge Creation*, Routledge.

Boschma, R., Minondo, A., Navarro, M. (2012), 'The emergence of new industries at the regional level in Spain: A proximity approach based on product relatedness', *Economic Geography*, N° 89(1), pp. 29–51.

Boschma, R., Wenting, R. (2007), 'The spatial evolution of the British automobile industry: does location matter?', *Industrial and Corporate Change*, N° 16(2), pp. 213–238.

Bravo-Biosca, A., Criscuolo, C., Menon, C. (2013), 'What Drives the Dynamics of Business Growth?', *OECD Science, Technology and Industry Policy Papers*, N° 1.

Breschi, S., Lissoni, F., Malerba, F. (2003), 'Knowledge-relatedness in firm technological diversification', *Research Policy*, N° 32, pp. 69–87.

Bresnahan, T. F. (2012), '*Generality, recombination and reuse', in Lerner*, J., Stern, S. (eds.), The rate and direction of inventive activity revisited, University of Chicago Press, Chicago, pp. 611–656.

Broadberry, S. N. (1994), 'Technological leadership and productivity leadership in manufacturing since the Industrial revolution: Implications for the convergence debate', *Economic Journal*, N° 104(423), pp. 291–302.

Buckley, P. J., Clegg, J., Wang, C. (2007), 'Is the relationship between inward FDI and spillover effects linear? An empirical examination of the case of China', *Journal of International Business Studies*, N° 38(3), pp. 447–459.

Buenstorf, G., Klepper, S. (2010), 'Why does entry cluster geographically? Evidence from the US tire industry', *Journal of Urban Economics*, N° 68(2), pp. 103–114.

Cadot, O., Carrère, C., Strauss-Kahn, V. (2011), 'Export diversification: What's behind the hump?', *Review of Economics and Statistics*, N° 93(2), pp. 590–605.

Caldarelli, G., Cristelli, M., Gabrielli, A., Pietronero, L., Scala, A., Tachella, A. (2012), 'A network analysis of countries' export flows: firm grounds for the building blocks of the economy', arXiv:1108.2590v2.

Cantner, U., Westermann, G. (1998), 'Localized technological progress and industry structure: An empirical approach', *Economics of Innovation and New Technology*, N° 6(2-3), pp. 121–146.

Cantwell, J. (1989), *Technological innovation and multinational corporations*.

Castaldi, C., Frenken, K., Los, B. (2014), 'Related Variety, Unrelated Variety and Technological Breakthroughs: An analysis of US State-Level Patenting', *Regional Studies*, N° 49(5), pp 767-781.

Chung, W., Yeaple, S. (2008), 'International knowledge sourcing: evidence from U.S. firms expanding abroad', *Strategic Management Journal*, N° 29(11), pp. 1207–1224.

Coad, A., Daunfeldt, S.-O., Hölzl, W., Johansson, D., Nightingale, P. (2014), 'High-growth firms: introduction to the special section', *Ind Corp Change*, N° 23(1), pp. 91–112.

Cohen, W. M., Levinthal, D. A. (1989), 'Innovation and Learning: The Two Faces of R&D', *The Economic Journal*, N° 99, pp. 569–596.

Cohen, W. M., Levinthal, D. A. (1990), 'Absorptive Capacity: A New Perspective on Learning and Innovation', *Administrative Science Quarterly*, N° 35, pp. 128–152.

Cohen, W. M., Nelson, R. R., Walsh, J. P. (2002), 'Links and Impacts: The Influence of Public Research on Industrial R&D', *Management Science*, N° 48(1), pp. 1–23.

Colombelli, A., Quatraro, F., Krafft, J. (2014), 'The emergence of new technology based sectors in European regions: A proximity based analysis of nanotechnology', *Research Policy*, N° 43, pp. 1681–1696.

Coppens, F., Lagneaux, F., Meersman, H., Sellekaerts, N., Van de Voorde, E., Van Gastel, G., Vanelslander, T., Verhetsel, A. (2007), 'Economic Impact of Port Activity: A Disaggregate Analysis-The Case of Antwerp', National Bank of Belgium Working Paper, N° 110, 2007.

Cowan, R., Jonard, N. (2004), 'Network structure and the diffusion of knowledge', *Journal of Economic Dynamics and Control*, N° 28(8), pp. 1557–1575.

Damijan, J. P., Kostevc, C., Rojec, M. (2010), '*Does a subsidiary's network status affect its innovation activity? Evidence from post-socialist economies*', ICEI, Universidad Complutense de Madrid.

David, P. A. (1975), *Technical choice, innovation and economic growth*, Cambridge UK, Cambridge University Press.

De Groot, H. L., Poot, J., Smit, M. (2007), 'Agglomeration, innovation and regional development', *Tinbergen Institute Discussion Papers*, N° 79(3).

De Propris, L., Driffield, N. (2006), 'The importance of clusters for spillovers from foreign direct investment and technology sourcing', *Cambridge Journal of Economics,* N° 30(2), pp. 277–291.

De Waldemar, F. S., Poncet, S. (2013), 'Product relatedness and firm exports in China', *The world bank economic review.*

Di Maria, C., Van der Werf, E. (2008), 'Carbon leakage revisited: unilateral climate policy with directed technical change', *Environmental and Resource Economics*, N° 39(2), pp. 55–74.

Dosi, G. (1988), 'Sources, Procedures, and Microeconomic Effects of Innovation', *Journal of Economic Literature*, N° 26, pp. 1120–1171.

Dosi, G., Soete, L., Pavitt, K. (1990a), *The economics of technical change and international trade*, Harvester Wheatsheaf, New York.

Dosi, G., Soete, L., Pavitt, K. (1990b), *The innovation process: international and intersectoral differences and determinants*, in Dosi, G., Pavitt, K., and Soete, L. (eds.), The economics of technical change and international trade, Harvester Wheatsheaf, New York, pp. 75–113.

Driffield, N., Love, J. H. (2003), 'Foreign direct investment, technology sourcing and reverse spillovers', *The Manchester School*, N° 71(6), pp. 659–672.

Dunne, T., Roberts, M. J., Samuelson, L. (1988), 'Patterns of firm entry and exit in US manufacturing industries', *The RAND journal of Economics*, pp. 495–515.

Duranton, G., Puga, D. (2001), 'Nursery Cities: Urban Diversity, Process Innovation, and the Life Cycle of Products', *American Economic Review*, N° 91(5), pp. 1454–1477.

Ecorys (2009), *Study on European Energy-Intensive Industries – The Usefulness of Estimating Sectoral Price Elasticities*, Cambridge UK, Study on behalf of European Commission DG Enterprise & Industry.

Eisenhardt, K. M., Martin, J. A. (2000), 'Dynamic Capabilities: What Are They?', *Strategic Management Journa*l, N° 21, pp. 1105–1121.

Etro, F. (2007), 'Dynamic Competition and Endogenous Entry', in Etro, F., Competition, Innovation, and Antitrust: A Theory of Market Leaders and Its Policy Implications, pp. 131–169.

Etxaleku, N., Girbés, S. (2011), *Regional Innovation Report (Valencian Community), Regional Innovation Report*, Technopolis Group, UNU-Merit Maastricht University, Fraunhofer ISI.

European Commission (2010a), 'Europe 2020 Flagship Initiative Innovation Union', Green paper and COM documents, COM(2010) 546 final, Brussels.

European Commission (2010b), 'Youth on the Move. An initiative to unleash the potential of young people to achieve smart, sustainable and inclusive growth in the European Union', Green paper and COM documents, COM(201) 477 final, Brussels.

European Commission (2010c), 'Europe 2020. A European strategy for smart, sustainable and inclusive growth', Green paper and COM documents, COM(2010)2020, Brussels.

European Commission (2011a), 'A resource efficient Europe - Flagship initiative under the Europe 2020 Strategy', Green paper and COM documents, COM(2011) 21, Brussels.

European Commission (2011b), 'An Integrated Industrial Policy for the Globalisation Era. Putting Competitiveness and Sustainability at Centre Stage', Green paper and COM documents, COM(2011) 614, Brussels.

European Commission (2011c), 'Cohesion Policy 2014-2020: Investing in growth and jobs', Green paper and COM documents, COM(2011) 614, Brussels.

European Commission (2011d), 'Industrial Policy: Reinforcing competitiveness', Green paper and COM documents, COM(2011) 642 final, Brussels.

European Commission (2012a), 'A stronger European Industry for Growth and Economic Recovery', Green paper and COM documents, COM(2012) 582/3, Brussels.

European Commission (2012b), *European Competitiveness Report 2012: Reaping the benefits of globalization*, Luxembourg.

European Commission (2014a), *Regional Innovation Scoreboard 2014*, Brussels, Belgium, DG Enterprise and Industry, European Commission, European Union.

European Commission (2014b), For a European Industrial Renaissance, Green paper and COM documents, COM(2014) 14 final, Brussels.

European Patent Office (2015), *Annual Report 2014*.

Fallick, B., Fleischman, C. A., Rebitzer, J. B. (2006), 'Job-hopping in silicon valley: some evidence concerning the microfoundations of a high-technology cluster', *Review of Economics and Statistics*, N° 88, pp. 472–81.

Falvey, R., Foster, N., Greenaway, D. (2004), 'Imports, exports, knowledge spillovers and growth', *Economics Letters*, N° 85(2), pp. 209–213.

Feenstra, R. (2004), *Advanced International Trade*, Princeton, Princeton University Press.

Ferragina, A. M., Pittiglio, R., Reganati, F. (2014), 'Does multinational ownership affect firm survival in Italy?', *Journal of Business Economics and Management*, N° 15(2), pp. 335–355.

Ferrari, M. R. (1999), *Small Enterprise Clusters for Local Development in Transition Context: the Case of Romania*, Milan, Bocconi University.

Figueiredo, O., Guimarães, P., Woodward, D. (2002), 'Home-field advantage: location decisions of Portuguese entrepreneurs', *Journal of Urban Economics*, N° 52, pp. 341–361.

Firgo, M., Mayerhofer, P. (2015), *Wissensintensive Unternehmensdienste, Wissens-Spillovers und regionales Wachstum. Final Report, part 1: Wissens-Spillovers und regionale Entwicklung – welche strukturpolitische Ausrichtung optimiert das Wachstum?*, Project Report, Austrian Institute of Economic Research.

Fleming, L., Sorenson, O. (2003), 'Navigating the Technology Landscape of Innovation', *Sloan Management Review*, Winter, pp. 15–23.

Florida, R. (1997), 'The globalization of R&D: Results of a survey of foreign-affiliated R&D laboratories in the USA', *Research policy*, N° 26(1), pp. 85–103.

Foray, D., David, P. A., Hall, B. H. (2011), 'Smart specialisation', MTEI Working Paper, N°1, 2011.

Foray, D., Goenaga, X. (2013), 'The Goals of Smart Specialisation.', JRC S3 Policy Brief Series No. 01, 2013.

Frenken, K., Boschma, R. (2011), *Technological relatedness and regional branching*, in Bahelt, H., Feldman, M. P., Kogler, D. F. (eds.), Dynamic Geographies of Knowledge Creation and Innovation, London, Taylor & Francis.

Frenken, K., Van Oort, F., Verburg, T. (2007), 'Related Variety, Unrelated Variety and Regional Economic Growth', *Regional Studies*, N° 41(5), pp. 685–697.

Friesenbichler, K. S. (2014), 'EU Accession, Domestic Market Competition and Total Factor Productivity. Firm Level Evidence', WIFO Working Paper, N° 492, 2014.

Friesenbichler, K. S., Böheim, M., Laster, D. C. (2014), 'Market Competition in Transition Economies: A Literature Review', WIFO Working Paper, N° 477, 2014.

Friesenbichler, K. S., Hölzl, W. (2014), *High growth firms, firm dynamics and industrial variety -Regional evidence from Austria*, 54th ERSA Conference, St. Petersburg.

Gaulier, G., Zignago, S. (2010), 'BACI: International Trade Database at the Product-level', CEPII Working Paper, N° 23, 2010.

Gerlagh, R., Kuik, O. (2007), *Carbon leakage with international technology spillovers*.

Girma, S., Greenaway, D., Wakelin, K. (2001), 'Who benefits from foreign direct investment in the UK?', *Scottish Journal of Political Economy*, N° 48(2), pp. 119–133.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., Shleifer, A. (1991), 'Growth in cities', National Bureau of Economic Research Working Paper, N° 3787, 1991.

Görg, H., Strobl, E. (2003), 'Footloose'multinationals?', *The Manchester School*, N° 71(1), pp. 1–19.

Greene, W. (2010), 'Testing hypotheses about interaction terms in nonlinear models', *Economics Letters*, N° 107(2), pp. 291–296.

Guardiola, G. G.-A. (2013), *Relevant aspects in european port competition: cases of Antwerp and Barcelona*.

Hall, P. A., Gingerich, D. W. (2009), 'Varieties of Capitalism and Institutional Complementarities in the Political Economy: An Empirical Analysis', *British Journal of Political Science*, N° 39(03), pp. 449.

Hall, P. A., Soskice, D. (2001), *Varieties of Capitalism: The Institutional Foundations of Comparative Advantage*, Oxford, Oxford University Press.

Hanel, R., Kauffman, S., Thurner, S. (2007), 'Towards a physics of evolution: Existence of gales of creative destruction in evolving technological networks', arXiv: physics/ 0703103v1 8.

Hanushek, E. A., Woessmann, L. (2012), 'Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation', *Journal of Economic Growth*, N° 17(4), pp. 267–321.

Harzing, A. (2002), 'Acquisitions versus greenfield investments: International strategy and management of entry modes', *Strategic Management Journal*, N° 23(3), pp. 211–227.

Hausmann, R., Hidalgo, C. A. (2011), 'The network structure of economic output', *Journal of Economic Growth*, N° 16, pp. 309–342.

Hausmann, R., Hwang, J., Rodrik, D. (2007), 'What you export matters', *Journal of Economic Growth*, N° 12(1), pp. 1–25.

Hausmann, R., Klinger, B. (2006), *Structural transformation and patterns of comparative advantage in the product space*.

Hausmann, R., Klinger, B. (2007), 'The structure of the product space and the evolution of comparative advantage', CID Harvard University Working Paper, N° 146, 2007.

Hausmann, R., Rodrik, D. (2003), 'Economic development as self-discovery', *Journal of Development Economics*, N° 72, pp. 603–633.

Helfat, C. E., Raubitschek, R. S. (2000), 'Product sequencing: co-evolution of knowledge, capabilities and products', *Strategic Management Journal*, N° 21, pp. 961–979.

Henrekson, M., Johansson, D. (2010), 'Gazelles as job creators: a survey and interpretation of the evidence', *Small Business Economics*, N° 35(2), pp. 227–244.

Hidalgo, C. A. (2009), 'The dynamics of economic complexity and the product space over a 42 year period', CID Harvard University Working paper, N° 189, 2009.

Hidalgo, C. A., Hausmann, R. (2009), 'The building blocks of economic complexity', *Proceedings of the National Academy of Sciences of the United States*, N° 106(26), pp. 10570–10575.

Hidalgo, C. A., Klinger, B., Barabási, A.-L., Hausmann, R. (2007), 'The product space conditions the development of nations', *Science,* N° 317(5837), pp. 482–487.

Huber, P., Reinstaller, A., Unterlass, F., Ebersberger, B. (2010), *Study on mobility patterns and career paths of EU researchers: Industrial researcher mobility study.*, Brussels, European Commission, DG Research Directorate C.

Hunt, J., Gauthier-Loiselle, M. (2008), 'How Much Does Immigration Boost Innovation?', National Bureau of Economic Research Working Paper, N° 14312, 2008.

Ianoş, I., Cercleux, A.-L., Pintilii, R.-D. (2010), 'Remarks on identity building of rural and urban communities in the Bucharest metropolitan area', Analele UniversităŃii din Oradea, Seria Geografie, Year XX.

Inui, T., Kneller, R., Matsuura, T., McGowan, D. (2009), *Globalization, productivity and plant exit-evidence from Japan*, ESRI, Cabinet Office and Nihon University.

Jacobs, J. (1969), *The economy of cities*, Random House.

Jankowska, A., Nagengast, A., Perea, J. R. (2012), 'The Product Space and the Middle-Income Trap: Comparing Asian and Latin American Experiences', OECD Development Centre Working Paper 311, http://www.oecd.org/dev/50249524.pdf.

Javorcik, B. S. (2004), 'Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages', *American economic review*, pp. 605–627.

Kauffman, S., Thurner, S., Hanel, R. (2008), 'The evolving web of future wealth', *Scientific American* (online), http://www.sciam.com/article.cfm?id=the-evolving-web-of-future-wealth.

Kaufmann, A., Tödtling, F. (2000), 'Systems of Innovation in Traditional Industrial Regions: The Case of Styria in a Comparative Perspective', *Regional Studies*, N° 34(1), pp. 29–40.

Kemp, R., Schot, J. W., Hoogma, R. (1998), 'Regime shifts to sustainability through processes of niche formation', Technology Analysis and Strategic Management, 10, S. 175–196.

Ketels, C. (2007), The Role of clusters in the chemical industry, Harvard Business School, EPCA.

Kim, L., Nelson, R. R. (2000), *Technology, learning, and innovation: Experiences of newly industrializing economies*, Cambridge University Press.

Klepper, S. (2001), 'Employee startups in high-tech industries', *Industrial and Corporate Change*, N° 10(3), pp. 639–674.

Klepper, S. (2006), 'The evolution of geographic structure in new industries', *Revue OFCE*, June, pp. 135–158.

Klepper, S. (2007), 'Disagreements, spinoffs, and the evolution of Detroit as the capital of U.S. automobile Industry', *Management Science*, N° 53(4), pp. 616–631.

Klepper, S. (2010), 'The origin and growth of industry clusters: The making of Silicon Valley and Detroit', *Journal of Urban Economics*, N° 67, pp. 15–32.

Klepper, S., Buenstorf, G. (2010), 'Why does entry cluster geographically? Evidence from US tire industry', *Journal of Urban Economics*, N° 68, pp. 103–114.

Klepper, S., Simons, K. L. (2000), 'Dominance by birthright: Entry of prior radio producers and competitive ramifiacations on the U.S. television receiver industry', *Strategic Management Journal*, N° 21, pp. 997–1016.

Knell, M., Shrolec, M. (2005), 'Innovation Cooperation and Foreign Ownership in the Czech Republic', mimeo.

Kogler, D. F., Rigby, D. L., Tucker, I. (2013b), 'Mapping Knowledge Space and Technological Relatedness in US Cities', *European Planning Studies*, N° 21(9), pp. 1374–1391

Koo, J. (2007), 'Determinants of localized technology spillovers: role of regional and industrial attributes', *Regional Studies*, N° 41(7), pp. 995–1011.

Krueger, A. B., Lindahl, M. (2000), *Education for growth: why and for whom?*, National Bureau of Economic Research.

Krueger, D., Kumar, K. B. (2004), 'Skill-Specific rather than General Education: A Reason for US-Europe Growth Differences?', *Journal of Economic Growth*, N° 9, pp. 167–207.

Kuemmerle, W. (1999), 'The drivers of foreign direct investment into research and development: an empirical investigation', *Journal of international business studies*, pp. 1–24.

Lall, S. (2001), *Competitiveness, Technology and Skills*, ERIC.

Lazonick, W. (2002), 'Innovative Enterprise and Historical Transformation', *Enterprise Soc,* N° 3(1), pp. 3–47.

Leo, H., Seon, P. (2011), Regional Innovation Report (Styria), Regional Innovation Report, Technopolis Group, UNU-Merit Maastricht University, Fraunhofer ISI.

Malerba, F. (2002), 'Sectoral systems of innovation and production', *Research policy*, N° 31(2), pp. 247–264.

Marchese, M., Potter, J. (2010), 'A Review of Local Economic and Employment Development Policy Approaches in OECD Countries: Executive Summary and Synthesis of Findings', OECD Local Economic and Employment Development (LEED) Working Papers , N° 05, 2010.

Marshall, A., Guillebaud, C. W. (1961), *Principles of economics*, London; New York, Macmillan for the Royal Economic Society.

Martin, R., Sunley, P. (2006), 'Path dependence and regional economic evolution', *Journal of economic geography*, 2006, N° 6(4), pp. 395–437.

Marvasi, E. (2013), 'The Sophistication of China's Exports, Imports and Intermediate Products', *The Chinese Economy, Springer*, pp. 181–209.

Maskell, P., Malmberg, A. (1999), 'Localised learning and industrial competitiveness', *Cambridge Journal of Economics*, N° 23(2), pp. 167–186.

Mayerhofer, P., Fritz, O., Platsch, D. (2007), '*Twin-City' Wien-Bratislava. Teil 2: Wettbewerbsfähigkeit und Arbeitsmarkt der zentraleuropäischen 'Twin-City' Wien-Bratislava im europäischen Vergleich: Eine Bestandsaufnahme,* Vienna, WIFO Monograph.

McCann, P., Ortega-Argilés, R. (2013), 'Smart Specialization, Regional Growth and Applications to European Union Cohesion Policy', *Regional Studies*, N° 0(0), S. 1–12.

Mehta, A., Felipe, J. (2014), 'Education and the Journey to the Core: Path Dependence or Leapfrogging?', SSRN Scholarly Paper, Rochester (NY), http://papers.ssrn.com/abstract=2467895.

Menzel, M.-P. (2008), 'Dynamic proximities - changing relations by creating and bridging distances', *Papers in Evolutionary Economic Geography*, N° 08.16.

Milgrom, P., Roberts, J. (1990), 'The Economics of Modern Manufacturing: Technology, Strategy, and Organization', *American Economic Review*, N° 80, pp. 511–28.

Milgrom, P., Roberts, J. (1995), 'Complementarities and fit: strategy, structure, and organizational change in manufacturing', *Journal of Accounting and Economics*, N° 19, pp. 179–208.

Moen, J. (2005), 'Is Mobility of Technical Personnel a Source of R&D Spillovers', *Journal of Labor Economics*, N° 23, pp. 81–114.

Mowery, D. (2009), '*What does economic theory tell us about mission-oriented R&D?*', in Foray, D. (eds.), The New Economics of Technology Policy, Edward Elgar, Aldershot.

Mundlak, Y. (1978), 'On the Pooling of Time Series and Cross Section Data', *Econometrica*, N° 46(1), pp. 69–85.

Narula, R. (2011), '*Attracting and embedding R&D in multinational firms: policy options for EU new member states*', in: Radosevic S., Kaderabkova, A. (eds), The Challenge for European Innovation Policy: Cohesion and Excellence viewed from a Schumpeterian Perspective, Edward Elgar Publ, Aldershot, pp. 150–175.

Navaretti, G. B., Tarr, D. G. (2000), 'International knowledge flows and economic performance: a review of the evidence', *The World Bank Economic Review,* N° 14(1), pp. 1–15.

Neffke, F., Hartog, M., Boschma, R., Henning, M. (2013), *Agents of structural change*, mimeo.

Neffke, F., Henning, M. (2008), 'Revealed relatedness: Mapping industry space', *Papers in Evolutionary Economic Geography,* N° 08-19.

Neffke, F., Henning, M., Boschma, R. (2011), 'How do regions diversify over time? Industry relatedness and the development of new growth paths in regions', *Economic Geography*, N° 87(3), pp. 237–265.

Neffke, F., Henning, M., Boschma, R., Lundquist, K.-J., Olander, L.-O. (2011), 'The Dynamics of Agglomeration Externalities along the Life Cycle of Industries', *Regional Studies*, N° 45(1), pp. 49–65.

Nelson, R. (1991), 'Why do firms differ, and how does it matter?', *Strategic Management Journal*, N° 12, pp. 61–74.

Nelson, R., Winter, S. (1982), *An Evolutionary Theory of Economic Change*, Boston, Belknap, Harvard University Press.

Nightingale, P., Coad, A. (2013), 'Muppets and gazelles: political and methodological biases in entrepreneurship research', *Industrial and Corporate Change*, N° 23(1), pp. 113–143.

Nightingale, P., Coad, A. (2014), The myth of the science park economy - Demos Quarterly, http://quarterly.demos.co.uk/article/issue-2/innovation-and-growth/.

Ning, L., Prevezer, M., Wang, Y. (2014), *Technological diversification in China: Based on Chinese patent analysis during 1986-2011*.

Nooteboom, B. (2000), *Learning and innovation in organizations and economies*, Oxford, Oxford University Press.

Papke, L. E., Wooldridge, J. M. (1996), 'Econometric methods for fractional response variables with an application to 401 (k) plan participation rates', *Journal of Applied Econometrics*, N° 11(6), pp. 619–632.

Papke, L. E., Wooldridge, J. M. (2008), 'Panel data method for fractional response variables with an application to test pass rates', *Journal of Econometrics*, N° 145, pp. 121–133.

Pen, C.-J., Hoogerbrugge, M. (2012), *Economic Vitality of Bucharest*, The Hague, European Metropolitan Network Insitute.

Porter, M. (1998), 'Clusters and the New Economics of Competition', *Harvard Business Review*, 1998, Reprint 98609, pp. 77–90.

Porter, M. E. (1996), 'Competitive Advantage, Agglomeration Economies, and Regional Policy', *International Regional Science Review*, N° 19(1-2), pp. 85–90.

Power, D. (2011), *The European Cluster Observatory: Priority sector report: creative and cultural industries*, Luxembourg, Directorate-General for Enterprise and Industry, European Commission, EUR-OP.

Prytherch, D. L., Boira Maiques, J. V. (2009), 'City profile: Valencia', *Cities*, N° 26(2), pp. 103–115.

Psacharopoulos, G., Patrinos, H. A. (2004), 'Returns to investment in education: a further update', *Education economics*, N° 12(2), pp. 111–134.

Ranga, M. (2012), *Regional Innovation Report (RO32 Bucharest - Ilfov), Regional Innovation Report*, Technopolis Group, UNU-Merit Maastricht University, Fraunhofer ISI.

Reinstaller, A. (2015), 'Local capabilities and competitiveness in international trade: A product space view', submitted manuscript.

Reinstaller, A., Hoelzl, W., Kutsam, J., Schmid, C. (2012), 'The development of productive structures of EU Member States and their international competitiveness.', Report prepared under Specific Contract No SI2-614099 implementing the Framework Contract ENTR/2009/033., Brussels, European Commission, DG Enterprise and Industry.

Reinstaller, A., Unterlass, F. (2011), *Sectoral Innovation Modes and the State of Economic Development: Implications for Innovation Policy in the New Member States*, in: Radosevic S., Kaderabkova, A. (eds), The Challenge for European Innovation Policy: Cohesion and Excellence viewed from a Schumpeterian Perspective, Edward Elgar Publ, Aldershot, pp. 77–111.

Reniers, G. L., Ale, B. J. M., Dullaert, W., Soudan, K. (2009), 'Designing continuous safety improvement within chemical industrial areas', *Safety Science*, N° 47(5), pp. 578–590.

Rigby, D. L. (2013), 'Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes', *Regional Studies*, pp. 1–16.

Rodrik, D. (2004), 'Industrial Policy for the Twenty-First Century.', KSG Faculty Research Working Paper, N° RWP04-047, 2004.

Rosenberg, N. (1990), 'Why Do Firms Do Basic Research (with their Own Money)?', *Research Policy*, N° 19, pp. 165–174.

Sadik, A. T., Bolbol, A. A. (2001), 'Capital flows, FDI, and technology spillovers: evidence from Arab countries', *world Development*, N° 29(12), pp. 2111–2125.

Saviotti, P. P., Frenken, K. (2008), 'Export variety and the economic performance of countries', *Journal of Evolutionary Economics*, N° 18(2), pp. 201–218.

Schott, P. K. (2004), 'Across-product versus within-product specialization in international trade', *The Quarterly Journal of Economics*, pp. 647–678.

Schumpeter, J. A. (1934), *The Theory of Economic Development*, Cambridge MA, Harvard University Press.

Shirotori, M., Tumurchudur, B., Cadot, O. (2010), 'Revealed factor intensity indices at the product level', *UNCTAD Policy Issues in International Trade and Commodities Study Series*, N° 44.

Sinha, U. B. (2009), 'Strategic licensing, exports, FDI, and host country welfare', *Oxford Economic Papers*,.

Song, L., Almeida, P., Wu, G. (2003), 'Learning-by-Hiring: When is mobility more likely to facilitate inter-firm knowledge transfer', *Management Science*, N° 49, pp. 351–365.

Storper, M. (1995), 'The Resurgence of Regional Economies, Ten Years Later: The Region as a Nexus of Untraded Interdependencies', *European Urban and Regional Studies*, N° 2(3), pp. 191–221.

Sutton, J., Trefler, D. (2011), 'Deductions from the Export Basket: Capabilities,Wealth and Trade', National Bureau of Economic Research Working Paper, N° 16834, 2011.

Teece, D., Pisano, G., Shuen, A. (1997), 'Dynamic Capabilities and Strategic Management', *Strategic Management Journal*, N° 18(7), pp. 509–533.

Til, J. Van (2012), Regional Innovation Report: Flanders, Regional Innovation Report, Technopolis Group, UNU-Merit Maastricht University, Fraunhofer ISI.

United Nations (2002), *Classification by Broad Economic Categories*, Department of Economic and Social Affairs.

Unterlass, F., Reinstaller, A., Huber, P., Janger, J., Hranyai, K., Strauss, A., Stadler, I. (2013), *Remuneration Cross-Country Report (WP4) – Support for Continued Data Collection and Analysis Concerning Mobility Patterns and Career Paths of Researchers*, Vienna, WIFO - Idea Consult.

Van Looy, B., Vereyen, C., Schmoch, U. (2014), *Patent Statistics: Concordance IPC V8 – NACE REV.2*.

Van Oort, F., de Geus, S., Dogaru, T. (2014), 'Related Variety and Regional Economic Growth in a Cross-Section of European Urban Regions', *European Planning Studies*, N° 23(6), pp. 1–18.

Van Wassenhove, L., Lebreton, B., Letizia, P. (2007), *A Paradigm Shift: Supply Chain Collaboration and Competition in and between Europe's Chemical Clusters*, EPCA - European Petrochemical Association.

Villaverde, J., Maza, A. (2015), 'The determinants of inward foreign direct investment: Evidence from the European regions', *International Business Review*, N° 24(2), pp. 209–223.

Wadhwa, V., Saxenian, A., Rissing, B., Gereffi, G. (2008), 'Skilled immigration and economic growth', *Applied Research in Economic Development*, N° 5, pp. 6–14.

Weitzman, M. L. (1998), 'Recombinant growth', *Quarterly Journal of Economics*, N° 113(2), pp. 331–360.

Wooldridge, J. M. (2005), 'Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity', *Journal of Applied Econometrics*, N° 20, pp. 39–54.

Zahra, S. A., George, G. (2002), 'Absorptive capacity: A review, reconceptualization, and extension', *Academy of management review*, N° 27(2), pp. 185–203.

Zahra, S. A., Ireland, R. D., Hitt, M. A. (2000), 'International expansion by new venture firms: International diversity, mode of market entry, technological learning, and performance', *Academy of Management journal*, N° 43(5), pp. 925–950.

Zepeda, E. A., Marmolejo, F., Dewayne, M., Parellada, M. (2006), *Supporting the Contribution of Higher Education Institutions to Regional Development*, OECD.

Zucker, L. G., Darby, M. R., Torero, M. (2002), 'Labor Mobility from Academe to Commerce', *Journal of Labor Economics*, N° 20, pp. 629–60.

# A. APPENDIX

## A.1. EXCURSUS – REGIONAL CASE STUDIES

The regression analysis at the regional level in chapter 4 provided several insights into the emergence of industrial structures and its facilitating conditions. The growth of industries and the generation of employment requires growth opportunities, which emerge through spillovers via industrial linkages between firms that are geographically bounded (Frenken, Van Oort and Verburg 2007). While the spillovers themselves may take on various forms, such as face-to-face contacts, the exchange of goods and services, labour mobility that transfers tacit knowledge, structural indicators are able to identify the cornerstones of spillover processes. This refers to the question about the origin of spillovers. Does new knowledge and growth impetus come from firms of the same industry, from firms of another industry, or from firms of another industry which however operate related technologies?

This excursus compares the evolution of industrial structures in five regions in greater detail. Hence, the main focus is on structural and cluster policies, and how they interact with the regional industry evolution. The chosen *case-study approach* allows identifying the interplay of factors that would be beyond the scope of a regression analysis. Regressions are able to identify stylised development patterns and facilitating factors, but struggles to capture the dynamics of the switching between short and long run effects. The case-study approach also allows analysing the role of softer, policy related factors. For instance, these include the interplay of several policy fields that are hard to quantify, but have yet contributed to the emergence of industries. Methodologically, this chapter relies on an analysis of official statistics, policy reports and industry studies that sketch the cornerstones of the regional development pattern.

The remainder of this section is structured as follows. A short introduction will briefly summarise the regression results from chapter 4 and augment the arguments made with findings about regional development patterns and evolutionary economics. The second part will describe the qualitative selection process that was implemented to arrive at the regions that will be analysed. The third part will present the case studies, before the final section identifies the patterns that the regions have in common.

### Relevant approaches on economic development

The previous results show an interesting ambiguity with regard to the relatedness of products. On the one hand, the short run effects are driven by the product neighbourhood density, indicating that the development of new fields of specialisation depend on a region’s current capabilities related to those required to produce the product. Evidence for the patenting activity in the United States suggests that patents are increasingly concentrating in fewer technology classes and the distance between those classes is shrinking. This path dependence has implications on the technologies that regions operate. While some cities manage a fast transition from one knowledge core to another, the process of technological transition is relatively slow in most regions. Path dependence can either be seen as a reflection of technological competence, or as a source of structural inertia hampering economic adjustments and growth potential (Kogler, Rigby and Tucker 2013; Rigby 2013).

On the other hand, the long-run effects yield the opposite result. The development of comparative advantages tends to be driven by the diversification into more weakly related product varieties. This is in line with Saviotti and Frenken (2008), who argue that closely related products drive export growth and export performance in the short run, while weakly related products drive performance in the long run. In addition, unrelated and related industrial variety affect the way how economic systems respond to economic crisis. Unrelated variety implies a broader industrial portfolio, which renders an economy more resilient to increases in unemployment in times of crisis. Related variety can be associated with capabilities to achieve economic growth in the short and medium run (Frenken, Van Oort and Verburg 2007).

These opposite effects raise the question about the underlying mechanisms at the tipping point. While product relatedness facilitates the entry of existing product lines in international markets, it also shows that it tames structural adjustments by creating a lock-in situation. What is the interplay between the deepening and sophistication of existing production structures and the emergence of new activities? In other words, what factors help overcome path dependence if it hampers industrial growth? If regions are strongly specialised, this may require abandoning technologies, which is most likely to occur at the edges of the knowledge core occupied by a city or region (Rigby 2013). This is of particular relevance in regions that struggle with their structural development and aim at designing policies for ‘industrial rejuvenation’. Case study evidence from phoenix industries (i.e. industries that re-emerged after a prolonged period of decline) paints a picture of decentralisation processes, the establishment of linkages between small and large firms and the creation of clusters. Path dependence matters insofar that the technology base serves as a basis for diversification, which often occurs after policy initiatives (Amison and Bailey 2013).

Phoenix industries are a special case of the cluster literature, however. There is a bulk of literature that more generally discusses *industrial clusters* in which knowledge spillovers occur. For instance, Marshall and Guillebaud (1961) stated that the concentration of an industry in a region supports linkages between firms, leads to labour market pooling and creates specialized suppliers. These contribute to a region's economic performance. More recent cluster concepts predict that the interplay of competition and industrial variety drive regional economic performance (Porter 1998, 1996). This contrasts the industry agglomeration reasoning, and argues that economic performance is driven by factors that come from outside the industry. A meta-study on urban growth by De Groot, Poot, and Smit (2007) revisits research findings for Marshall's (specialization), Jacobs's (diversity) and Porter's (competition) externalities as explanations for innovation and regional growth. The results are rather mixed, and depend on the data and chosen indicators, study design and control variables. Depending on the setting, any of these approaches may offer insights into important drivers of economic dynamism (Glaeser et al. 1991).

A slightly different perspective comes from the *entrepreneurship* literature, which argues that diversification into new activities is typically driven by new firms (Dunne, Roberts and Samuelson 1988; Malerba 2002). This implies that the potential for the development of a regional cluster depends on the regional entrepreneurial base. While diversification that originates from existing firms can be achieved by spin-offs, diversification into more unrelated activities requires other kinds of start-ups, which are for instance FDI driven and is made possible by other externalities (Buenstorf and Klepper 2010), such as agglomeration economies and proximity to major urban centres (Figueiredo, Guimarães and Woodward 2002). *Evolutionary economics* finds that industrial dynamism such as rates of high growth firms and labour markets turbulence, is linked to both industrial re-structuring processes and total employment (Bravo-Biosca, Criscuolo and Menon 2013; Coad et al. 2014; Henrekson and Johansson 2010). For instance, findings for Austria link firm dynamism at the regional level to employment growth and workforce dynamics (Friesenbichler and Hölzl 2014). Combining cluster and entrepreneurship literature suggests that the supply of capable entrants, the availability of localized knowledge, and production externalities influence where entrants originate and locate. Capable entrants are more likely to be present around existing producers and in more populated regions. Also, there seems to be a self energising process. The presence of cluster externalities influences firm profitability and entry, which again influences agglomeration externalities. However, this is an endogenous process that occurs within the boundaries of entrants' capabilities (Buenstorf and Klepper 2010).

The diversification of regional industrial structures hinges on the emergence of new technologies, which can be innovative in a sense that they push a hypothetical technological frontier, or can be part of a catching-up process where existing technologies are implemented. The role of innovation or implementation depends on the stage of development. As an economy approaches the technology frontier, competition between firms and switching into unrelated activities with smaller, technology intensive firms may become more important. Countries in catching-up processes, which are in earlier stages of development, may rather pursue an investment-based strategy, with long term relationships, high average size and age of firms, large average investments, but little selection (Acemoglu, Aghion and Zilibotti 2004).

This may imply that specialisation and related variety becomes more important as countries approach the technological frontier, while unrelated variety plays a larger role in catching-up processes, where the establishment of more basic capabilities is dominant. In addition, this has implications on the human capital formation and education policies. As countries advance technologically, the firm dynamism increases due to shorter technology life cycles. This means that the regional workforce requires *skills* that are flexibly transferrable from one task to another. Hence, countries in a catching up process should establish a skill-specific, vocational education, while technologically advanced countries may rather implement a concept-based, general education (Krueger and Kumar 2004).

Another strand of literature is *institutional economics*, emphasising that both inter- and intra-industry diversification does not occur in a vacuum. Institutional structures shape the impact on the direction of industrial evolution. Firm performance is the outcome of the interaction with other actors in multiple spheres of the political economy (e.g., to raise finance, in their industrial relations, to form human capital or via inter-firm relations). One can distinguish between two extremes of the institutional design. On the one hand, there are 'liberal market economies' where relations between firms and other actors are coordinated mainly by competitive markets and price mechanisms. On the other hand, there are 'coordinated market economies', where firms engage in more strategic interaction with trade unions, suppliers of finance, and other actors (Hall and Gingerich 2009; Hall and Soskice 2001). Such institutional structures affect the likelihood of a country gaining a comparative advantage in sectors that are close or far from an existing industrial structure. It has been shown that relatedness is a stronger driver of diversification into new products in coordinated market economies, while liberal market economies show a higher probability to move in more unrelated industries (Boschma and Capone 2014).

To sum up, the literature remains ambiguous about the sources for, and patterns of industrial change. While path dependence, specialisation and the deepening of activities seems to provide short run growth, the establishment of new structures and the exploration of new activities are relevant for long run performance. While coordinated market economies seem to provide advantages in the exploitation of existing strengths, liberal market economies have advantages overcoming the inertia that path dependence may imply. New firms and technologies are often the driver of diversification processes that increase both related and unrelated variety. The closer an economy's technology base is to the technological frontier the more important specialisation seems to become to "push the frontier".

## Selection criteria

A series of case studies will aim to depict these mechanisms at the regional level. The sample was drawn from the universe of all regions in the European Union. A qualitative selection process was pursued to select regions for which the industrial diversification mechanisms will be illustrated.

First, the regions were selected with the aim to cover Member States geographically. The regions are located in Northern, Western, Southern and Eastern Europe. This criterion not only reflects different histories and development paths, but also illustrates differences in socio-demographic characteristics. Regions were required to be sufficiently large so that industrial evolution patterns would become visible. Hence, regions with fewer than 500,000 inhabitants were not considered in the selection.

Second, European regions differ in their innovation capabilities, which is why information from the Regional Innovation Scoreboard was used in the selection. Particular focus was on regions that changed their relative position in the ranking over time (information is available for the period between 2004 and 2014).

Third, regions with energy intensive and carbon-leakage affected industries were explicitly considered (see Box A.). This indicator is based on a list of industries exposed to carbon leakage, including both energy intensive and trade intensive industries. To distinguish between specialisation patterns stemming from energy intensive industries and trade intensive industries the analysis was amended by alternative classification schemes (e.g. Ecorys 2009). In regions with a high share of carbon-leakage affected industries, the industrial base is typically dominated by large, scale-intensive firms. This implies that scale-related cost competitiveness might be offset by little flexibility to adjust production structures due to high fixed costs. This increases the exposure to adverse effects of structural change. Structural path dependence also affects different reactions of regional economic challenges. For instance, a region may suffer from a drop in competitiveness in its core industry, which is then in decline. Policy makers are then typically required by the public to implement industrial rejuvenation policies that may or may not be successful.

Implementing these selection criteria identified five distinctive regions – the NUTS-2 code and the English name used henceforth in this study are provided in parentheses (see Figure A.1):

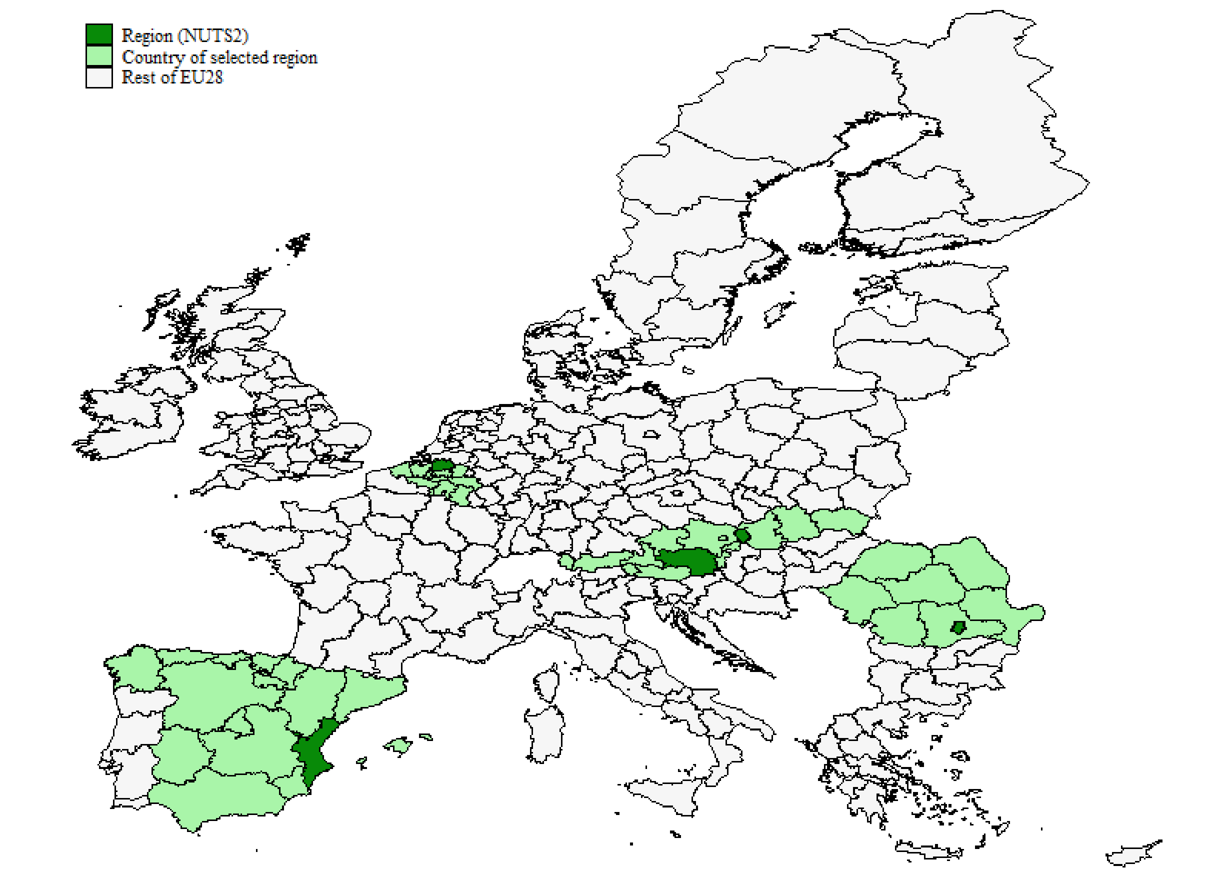
- Provincie Antwerpen (BE21; Antwerp),
- Bucuresti - Ilfov (RO32; Bucharest),
- Steiermark (AT22; Styria),
- Bratislavský kraj (SK01; Bratislava), and
- Communidad Valenciana (ES52; Valencia).

The chosen sample provides an interesting mix of regions with regard to regional characteristics. Valencia is a Southern region of Spain. Antwerp is a region of Belgium in the North-West of Europe. Both Styria and Bratislava are regions in Central Europe, the former in Austria and the latter in the Slovak Republic. Bucharest is the capital region of Romania in Eastern Europe. Antwerp, Styria and Valencia joined the European Union before the enlargement of the EU in 2004, Bratislava in 2004 and Bucharest in 2007.

The gross regional product per capita, a proxy for average economic activity, finds Styria and Antwerp relatively more developed. By 2011, Bratislava as a catching up region in Central-Eastern Europe has outperformed Valencia in Southern Europe. Bucharest's regional product per capita is lower, but the region is catching up fast. More generally, the growth figures follow the expected patterns – regions with lower per capita income levels grew faster than more developed regions (Acemoglu, Aghion and Zilibotti 2004).

However, the impact of the economic crisis on growth rates differs substantially across the regions in the sample. While growth only marginally dropped in Antwerp, Styria and Bratislava after 2008, Bucharest experienced a sharp decline in economic growth. The growth rate for Valencia turned negative, mirroring Spain's macro-economic performance in the crisis (see Table A.1).

**Figure A.1 Selected NUTS2 regions in EU-28**




*Source: Eurostat; Illustration by WIFO*

The unemployment rates indicate that especially Valencia, and to a lesser degree Bucharest struggle with labour market issues. Interpreting these figures against the background of country-specific levels of unemployment, Antwerp, Styria and Bratislava are below the national average, whereas the unemployment figures for Bucharest and Valencia are higher than the national average. Also the population density differs – while especially Bucharest and Antwerp are highly urbanised, Styria is rather sparsely populated. Valencia and Bratislava are in between.

The share of trade- and energy-intensive industries at significant risk of carbon leakage as well as the share of energy-intensive industries serve as an indicator for the degree of industrialisation. Especially Styria and Antwerp exhibit a risky profile in terms of the carbon leakage indicator, which can be explained by the established industrial structures. Bucharest and Bratislava underwent a structural transition process which led to the disappearance of emission intensive industries. The results for the regional energy intensity in 2011 shows similar results. In particular Antwerp ranks high – the region's energy intensity is 6$^{th}$ in the EU with a share of 21%. Valencia ranks 25$^{th}$ with 12.8%, and Bratislava 42$^{nd}$ with 11.2%.

**Table A.1 Overview of socio-economic indicators by region**

| REGION (NUTS-2 code) Geography | Antwerp (BE21) West | Valencia (ES52) South | Styria (AT22) Central European | Bucharest (RO32) East | Bratislava (SK01) Central European |
|---|---|---|---|---|---|
| Gross Domestic Product / Total population 1990[1] | 26583 | 14897 | 18749 | 3858 | 8109 |
| Gross Domestic Product / Total population 2011[1] | 34419 | 18161 | 27696 | 10786 | 22707 |
| Mean GDP Growth 1990-2008[1] | 1.6% | 1.6% | 2.2% | 6.2% | 5.4% |
| Mean GDP Growth 2009-2011[1] | 1.5% | -0.6% | 1.9% | 3.4% | 4.1% |
| Unemployment rate by NUTS 2 regions[2] | 6.2% | 28.0% | 4.0% | 7.8% | 6.4% |
| Unemployment rate from 15 to 24 years[2] | 19.1% | 56.3% | 8.7% | 26.1% | 19.7% |
| Unemployment rate 25 years or over[2] | 5.0% | 25.7% | 3.3% | 6.8% | 5.6% |
| Population Density 2012 (inhabitants per square kilometre)[2] | 643 | 217 | 74 | 1,297 | 297 |
| Population at 1 January by NUTS 2 regions 2014[2] | 1,809,412 | 4,956,427 | 1,214,927 | 2,282,968 [e] | 618,380 |
| Land area by NUTS 2 regions[2] | 2,867.0 | 23,254.5 | 16,401.0 | 1,821.0 | 2,053.0 |
| Carbon-leakage share[3, cl] | 62.8% | 50.6% | 62.8% | 43.9% | 48.6% |
| Energy Intensive Industries (Carbon-leakage Types A and/or B)[3, cl] | 21.8% | 12.8% | 5.2% | 2.3% | 11.2% |
| Population aged 25-64 with tertiary education attainment[2] | 35.4% | 30.8% | 17.5% | 33.1% | 37.5% |
| COUNTRY | Belgium | Spain | Austria | Romania | Slovakia |
| Gross Domestic Product / Total population 1990[1] | 22575 | 15165 | 22548 | 2963 | 4018 |
| Gross Domestic Product / Total population 2011[1] | 30110 | 20414 | 31953 | 4342 | 9163 |
| Mean GDP Growth 1990-2008[1] | 1.6% | 2.0% | 2.0% | 2.4% | 4.6% |
| Mean GDP Growth 2009-2011[1] | 1.6% | -0.7% | 1.9% | 0.8% | 3.5% |
| Unemployment rate[2] | 8.4% | 26.1% | 4.9% | 7.1% | 14.2% |
| Unemployment rate from 15 to 24 years[2] | 23.7% | 55.5% | 9.2% | 23.6% | 33.7% |
| Unemployment rate 25 years or over[2] | 7.0% | 23.7% | 4.2% | 5.9% | 12.5% |
| Population Density 2012 (inhabitants per square kilometre)[2] | 367 | 93 | 102 | 87 | 110 |
| Population at 1 January 2014[2] | 11,203,992 | 46,512,199 | 8,506,889 | 19,947,311[e] | 5,415,949 |
| Total land area[2] | 30,528 | 505,990.7 | 83,879.0 | 238,391.0 | 49,036.0 |
| Population aged 25-64 with tertiary education attainment[2] | 35,5% | 33,7% | 20,6% | 15,6% | 19,9% |

*Note: e = estimated; all data retrieved on 10th March 2015, cl = refers to carbon-leakage (share of trade- and energy-intensive industries at significant risk of carbon leakage) and energy-intensity list (see Box 6.1: Industries exposed to a significant risk of carbon leakage.in Appendix)*
*Source: 1) Cambridge Econometrics, 2) Eurostat (data for 2013), 3) WIFO calculations, Eurostat (Structural Business Statistics). Bureau van Dijk (Amadeus database; 2011)*

## Regional evidence

This section describes the regional diversification processes in greater detail. It draws on a semi-standardised approach. The initial part briefly explains the same dimensions for each region. These include the country specific setting and key indicators of the regional economy such as growth and unemployment rates. Also the emergence of the composition of the manufacturing and mining and quarrying sector will be shown. Data on service industries were often not available in earlier years, which is why the evolution of the private sector in the long run can only be shown for a minority of the cases. Additional information about the structure of the service sector will be presented for the final year, and – where possible – over time. In addition, the analysis will include the development of an employment-based Herfindahl-Hirschman index over time as a broad indicator for unrelated variety. The average establishment size serves as an indicator for scale economies and therefore entry barriers. In addition, the results from the Regional Innovation Monitor will be included to indicate the regions' technological capabilities (see Box 4.2). The second part will focus on a qualitative assessment of the idiosyncratic regional developments, which also includes the service sector. These sections will comprise of a sketch of structural challenges and developments, and the reaction of regional policy makers.

**Box A.1 The Regional Innovation Monitor and the data base**

The **Regional Innovation Scoreboard** is a regional extension of the Innovation Union Scoreboard (IUS), which replicates the methodology of the IUS at the regional level. The IUS gives a comparative assessment of the innovation performance at the country level of the EU Member States and other European countries. Innovation performance is measured by a composite indicator – the Summary Innovation Index – which summarises the performance of a variety of different indicators. The IUS distinguishes between three types of indicators – Enablers, Firm activities and Outputs – and eight innovation dimensions, capturing in total 25 indicators that are used to construct the composite index (European Commission 2014a).

The composite index of the Regional Innovation Scoreboard is used in the **Regional Innovation Monitor**, an initiative of the European Commission's Directorate General for Enterprise and Industry, which has the objective to describe and analyse innovation policy and performance trends across EU regions. The report groups the regions into different and distinct innovation performance clusters. The grouping is based on their relative performance on the Regional Innovation Index compared to the mean value of the European Union. The groups rely on the same thresholds in relative performance as the IUS. *Regional Innovation Leaders* are therefore regions which perform 20% or more above the EU average. *Regional Innovation Followers* are regions scoring between 90% and 120% of the EU average. *Regional Moderate Innovators* are regions performing between 50% and 90% of the EU average and *Regional Modest Innovators* score below 50% of the EU average (European Commission 2014a).

In addition, information provided by the **Structural Business Statistics** of Eurostat was used to describe changes in the industry structure over time. Since information on the service sector varied across regions and was not available for all periods, the analysis focused on industries in mining and quarrying and in manufacturing (i.e., 2-digit Nace Rev. 1.1. data for the sectors C + D).

Value added figures were not available at the industry (NACE Rev. 1) and NUTS2-digit level, which is why **employment data** was used instead. The variable used is "Number of persons employed" (V16110). The indicator is defined as the total number of persons who work in the observation unit (inclusive of working proprietors, partners working regularly in the unit and unpaid family workers), as well as persons who work outside the unit who belong to it and are paid by it (e.g. sales representatives, delivery personnel, repair and maintenance teams). It excludes manpower supplied to the unit by other enterprises, persons carrying out repair and maintenance work in the enquiry unit on behalf of other enterprises, as well as those on compulsory military service.

This indicator served as a basis to calculate **employment shares** and a Herfindahl-Index, a measure for market concentration. The Herfindahl-Index is calculated as the squared sum of industry shares in total employment. The indicator was rescaled so that it takes on a value of 100% if one industry employs the entire workforce of the sector, and a lower value if employment is less concentrated across industries. Due to data availability, mining and quarrying as well as manufacturing industries were considered in the computation of the index. As an indicator for the number of firms, a count of the **number of local units** active during at least a part of the reference period was used. Industry level employment data divided by the number of local units were used as an approximation for the **average establishment size** at the industry level.

### *Styria*

Styria is located in the South-East of Austria, and borders Slovenia and other Austrian provinces. With a regional domestic product per capita of €27,696, its economic activity is approximately 15% below the Austrian average. Between 1990 and 2011, the regional per capita product in constant prices grew by 48% (reference year: 2005).

In 2014, the region's population was 1,214,927; the capital city Graz had 265,000 inhabitants. The region is rather rural with a low population density of merely 75 inhabitants per square kilometre. At 4%, the region's unemployment rate was below the national average of 4.9% in 2013. The youth unemployment rate is only slightly above the unemployment rate for the segment of people older than 25 years, which indicates a labour market that relatively well matches supply with demand. The economic growth after the crisis remained relatively high – the post crisis growth rate of +1.9% is marginally below the long run average growth of +2.2% (see Table A.1).

The region's Economic activity shifted toward the service sector. Employment data is available for the years 1995 and 2007. Despite its increase in absolute numbers, manufacturing declined as a share of total employment from 36% in 1995 to 31% in 2007. In the same period, the employment shares of real estate, renting and business activities increased from 8% to 16%. Other subsectors of the private sector remained quite constant in the overall sector composition. In 2007, construction accounted for 10% (1995: 11%), wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods for 24% (1995: 25%), hotels and restaurants for 8% (1995: 9%), transport, storage and communications for 9% (1995: 8%), electricity for 1% of total employment (1995: 2%), and mining and quarrying for 0.4% (1995: 1%).

Not only the relevance in the sector real estate, renting and business activities increased, also its composition changed. At 76%, other business activities made for the bulk of employment within this subsector in 2007 (1995: 82%). Computer and related activities increased from 6% in 1995 to 9% in 2007, and R&D increased from 2% to 3% in the reference period. The subsector's employment share remained constant at 10% (1995: 9%). However, the number of establishments reflects this growth performance and points towards a deepening of activities. In 2007, there were 2,145 establishments in real estate, which is more than five times than in 1995. 113 establishments were in R&D (1995: 27; +319%), 1501 in computer and related activities (1995: 364; +312%), 365 in the renting of machinery and equipment (1995: 226; +62%). In 2007, 7,380 establishments were assigned to other business activities (1995: 2946; +151%). Overall, this indicates a shift towards real estate, renting and business activities, with knowledge intensive business services gaining relevance.

Total employment in manufacturing and mining and quarrying changed from 79,497 in 1995 to 102,253 in 2007 (+28.7%). The employment-based industry concentration across industries changed very little over time. The Herfindahl-Index was 8.7% in 2007 (1995: 9.2%). With an industry share of 15.3%, the manufacture of fabricated metal products was the largest industry in 1995; the industries average establishment size was 29 employees. Manufacture of machinery and equipment n.e.c. had a share of 14.1% (average establishment size: 42). Manufacture of basic metals made for 10.8% of employment in manufacturing, with an average establishment size of 233. In 2007, this industry made for 9.4% of the sector's employment with an average establishment size of 246. In 2007, the largest employer in the manufacturing sector was manufacture of machinery and equipment (13.3%), the manufacture of fabricated metal products (13.1%) and the manufacture of motor vehicles, trailers and semi-trailers (11.7%), which had an average establishment size of 178 (see Table A.2).

**Table A.2 Development of key manufacturing industries in Styria**

| Industry | Employment 1995 | Employment 2007 | Share 1995 | Share 2007 | Avg. Est. Size 1995 | Avg. Est. Size 2007 |
|---|---|---|---|---|---|---|
| DJ27;Manufacture of basic metals | 8613 | 9611 | 10.8% | 9.4% | 233 | 246 |
| DK29;Manufacture of machinery and equipment n.e.c. | 11183 | 13585 | 14.1% | 13.3% | 42 | 19 |
| DJ28;Manufacture of fabricated metal products, except machinery and equipment | 12176 | 13445 | 15.3% | 13.1% | 29 | 38 |
| DM34;Manufacture of motor vehicles, trailers and semi-trailers | 6025 | 11975 | 7.6% | 11.7% | 133 | 179 |

*Source: Eurostat SBS data, WIFO calculations*

In an EU-wide ranking, the Regional Innovation Monitor classifies Styria as an Innovation Follower, which is the second highest category behind Regional Innovation Leaders. Since 2004, the regional innovation performance has improved; the region is in the group that increased its composite index (RIS) between 2.5% and 15%. The region's performance indicators paint a mixed picture, however. On the one hand, the share of people with tertiary education and government research and development (R&D) expenditures is below the EU-average. In 2012, the share of the population aged 25-64 with tertiary education attainment was 17.9%, which is only slightly above the level of 2003 of 14.9% (Eurostat data). On the other hand, R&D financed by both private businesses and higher education facilities are above the EU mean, as is the number of patents per million inhabitants. The business environment in which innovation occurs has been assessed as stable and reliable. As to technology policy, innovation promotion has a long tradition in the manufacturing sector, but fall short in facilitating innovation in services as well as non-traditional sectors. This is insofar surprising as Styria was able to tap into new specialisation in (manufacturing related) knowledge-intensive business services, which is also strong when compared to the situation in other manufacturing dominated regions in Europe (based on SBS data). Hence Styria's strengths in (medium-tech) manufacturing expanded towards related services. This may serve as a basis for the implementation of smart manufacturing (Industry 4.0). Over and above industrial path dependence, this policy focus might hamper the diversification of the regional economy. Policy measures often hinge on cluster initiatives, and instruments focus on human capital building and internationalisation (Leo and Seon 2011).

**Assessment of the industry evolution**

The Styrian economy used to be dominated by predominantly state-owned manufacturing firms in the iron and steel industry. These highly vertically integrated firms had already lost their headquarter functions in the 1960s and 1970s to the advantage of Vienna. In the 1970s and 1980s, the industry faced a severe structural crisis due to the increase in oil prices and a drop in demand, which revealed operative inefficiencies. Also, the exposure to a new economic situation in the 1990s due to the fall of the Iron Curtain on its border contributed to structural challenges. At the end of the 1980s, large firms were (re-)privatised and downsized, which set the basis for corporate transformations. After a restructuring process, the new firm base could exploit growing demand from the mid 1990s. Wide parts of the economic activities could be maintained, even though planning functions, R&D and marketing/distribution functions had been largely lost. These structural challenges are mirrored by the region's poor economic growth until the 1990s, an unbalanced labour market, and little economic dynamism, expressed by a low rate of innovation and poor firm entry performance. In particular, the problems of the heavy industry mainly located in the northern part of Styria were affected by the structural crisis (Marchese and Potter 2010).

This led to a series of structural changes which centre on the changes from a Fordist system to a collaborative, SME-based structure in which systems of suppliers set prices and quality. This occurred in the 1980s, and is therefore not reflected in the present data series that begin in 1995. As the large firms were disintegrated and a decentralised firm base emerged, firms were required to focus on niche markets and specialise. The regional innovation pattern shifted away from firm specific technologies toward a regional innovation system, in which collaborations with universities and colleges play a crucial role. In addition, new industries were established mainly through cluster policies, which often met strong political support. For instance, despite "endogenous roots", a car producer cluster was established by foreign direct investments of a tier one car supplier. As a consequence, further investments by international car manufacturers followed (Kaufmann and Tödtling 2000). Also, knowledge intensive functions such as R&D or marketing that used to be conducted in-house in large companies have been outsourced. This led to the emergence of a knowledge-intensive service industry which is tightly linked to the region's manufacturing base.

While the decentralisation reduced the product range at the firm level, it also allowed for diversification at the regional economy level. There is also evidence that some firms conducting R&D have shifted away from a demand-pull to a science-push business model. This process was facilitated by regional government economic policies, which promoted cooperation and networks and new institutions of knowledge generation. Yet, there remains a rather high concentration of economic activity in a relatively small range of technology fields and industries (Marchese and Potter 2010).

This shift was made feasible by the relatively strong R&D capabilities that the private sector could use. There are several universities such as the Technical University of Graz, The University of Graz and the University of Leoben, a university for mining metallurgy and materials. In addition, applied colleges were established to provide human capital to the relatively new industries, especially the car industry (e.g., FH Joanneum). Even though the education system has continuously adjusted to provide adequately skilled human capital, there were reports of skills shortages in certain knowledge fields. To match labour demand with labour supply will continue to remain a challenge to local policy makers (Leo and Seon 2011). Over and above the increase in skills driven by the tertiary education and research system, the region's manufacturing base was benefitting from Austria's dual education system. The long established system combines apprenticeships in companies with compulsory training at a vocational school. This helped prevent human capital shortages by allowing especially larger firms to create the knowledge that they require.

By and large, the transformation of Styria resembles experiences from phoenix industries. The emergence of smaller firms pursuing open innovation strategies was important, because it allowed faster and cheaper innovation processes. Smaller firms also required an increased level of interaction across technologies (e.g., between the car industry and machinery and equipment), which occurred up and down supply chains, and also between larger and smaller firms (several tier one suppliers of the car industry interact with research facilities and smaller suppliers in the region). It also shows that historic and rather immobile investments in the region matter, and perhaps even pose a lock-in situation. The region's industrial rejuvenation was accompanied by a shift of economic activities towards the knowledge-intensive service industry. Finally, policies and the coordination of agents mattered, which concerns the restructuring of old industries, and the emergence of new ones (Amison and Bailey 2013).

*Bucharest*

Romania's capital region consists of i) Bucharest, the capital city which is the national political and administrative centre, and ii) Ilfov county, which is the surrounding area. The region exhibited a remarkable catching-up process (see Table A.1). With a regional domestic product per capita of 10,786 Euro in 2011, its economic activity increased substantially. Between 1990 and 2011, the regional per capita product in constant prices grew by a total of 180% (base year: 2005). This is mirrored by an average annual economic growth rate of +6.2% for the period between 1990 and 2008. Regional economic growth declined with the crisis, but was still positive at +3.4%. These figures should be interpreted with caution, however, The Romanian currency devaluated sharply between 1999 and 2005 against the Euro, and the exchange rate is somewhat stable only from 2009 onwards. The unemployment rate amounted to 7.8% in 2013, which is only slightly above the national average. Youth unemployment is high, however (26.1%).

In 2007, manufacturing accounted for 20% of the total economy. Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods accounted for 28%, real estate, renting and business activities for 24%, transport storage and communications for 11%, construction for 12%, hotels and restaurants for 3% and electricity, gas and water supply for 2%.

The industry concentration in the sectors manufacturing and mining and quarrying in the Bucharest region increased to a small degree. In 2000 (first year available), the employment based Herfindahl-index in manufacturing and mining and quarrying was 7.5%. In 2007, this value was slightly higher at 7.9%. Total employment in the manufacturing sector decreased by 26.9% from 260,930 employees in 1995 to 190,728 employees in 2007. Since unemployment rates remain relatively low, these dynamics in manufacturing point at a structural change towards the service industry, which is in line with observations for many transition economies (Friesenbichler, Böheim, and Laster 2014). In 2007, the largest manufacturing industries were the manufacture of food products and beverages with an employment share in the sector of 17.2%, followed by publishing, printing and reproduction of recorded media (10.2%), and the manufacture of wearing, apparel, dressing, dyeing of fur (9.4%). With an employment share of 12.9%, the apparel industry was the largest employer in manufacturing in 1995, followed by the food industry with 12.5% and machinery and equipment at 9.6% (see Table A.3).

**Table A.3 Development of key manufacturing industries in Bucharest – Ilfov**

| Industry | Employment 2000 | Employment 2007 | Share 2000 | Share 2007 | Avg. Est. Size 2000 | Avg. Est. Size 2007 |
|---|---|---|---|---|---|---|
| DE22;Publishing, printing and reproduction of recorded media | 22048 | 19365 | 8.4% | 10.2% | 22 | 10 |
| DK29;Manufacture of machinery and equipment n.e.c. | 24972 | 10622 | 9.6% | 5.6% | 103 | 25 |
| DA15;Manufacture of food products and beverages | 32605 | 32800 | 12.5% | 17.2% | 27 | 26 |
| DB18;Manufacture of wearing apparel; dressing; dyeing of fur | 33673 | 17862 | 12.9% | 9.4% | 47 | 19 |

*Source: Eurostat SBS data, WIFO calculations*

The Regional Innovation Monitor classifies the Bucharest region as a Moderate Innovator whose composite innovation score has been increasing. As a region in a catching-up country, it mainly pursues an investment driven growth strategy and imitates existing technologies (Acemoglu, Aghion and Zilibotti 2004). Yet, it still struggles with the establishment of an efficient public administration, which imposes economic, social, political, and structural challenges. Poor institutions have been identified as the single biggest challenge in innovation and diversification. In particular; regional innovation policies and formal institutions are lacking (Ranga 2012). However, the accession to the European Union has not only opened markets, but also facilitated institutional reform that facilitated the provision of a level playing field for entrepreneurs (Böheim and Friesenbichler 2014). The Regional Innovation Monitor identifies further challenges, such as the improvement of the region's connectivity via the expansion of transport infrastructure or arising social and environmental issues (Ranga 2012). In 2012, the share of the population aged 25-64 with tertiary education attainment was 32%. This reflects a substantial increase over the past decade – in 2003 the share was 22.6% (Eurostat data).

**Assessment of the industry evolution**

The regional economic structure is the result of economic transformations that began in December 1989 with the collapse of the socialist economic system. After macro-economic adjustments in the 1990s, Romania experienced rapid economic growth in the 2000s. Bucharest, such as Romania as a whole, shared the experiences of other countries with a communist legacy. The transition process changed the economic system to private sector allocation which replaced the command economy. This occurred mainly through restructuring of the formerly state owned enterprises and the establishment of a new firm base through facilitating firm entry and trade openness (Friesenbichler, Böheim, and Laster 2014; Ranga 2012).

The establishment of a new allocation system implied that economic inefficiencies were being addressed, and "labour hording" in inefficient firms became more difficult (Ferrari 1999). The restructuring – particularly in the mechanical, metallurgic and chemical industries in the period 1990-1995 – set labour free which led to high unemployment rates and the migration of a large part of the industrial labour force to the services sector (Ranga 2012). This aspect of the transition is reflected by the average establishment size in machinery and equipment, which fell from 103 to 25 employees between the years 2000 and 2007. Transition policies led to a firm-level productivity distribution which indicates higher efficiency levels. At the same time, new firms emerged, which often operate state-of-the-art production technologies that use less energy and cause lower CO2 emissions (Friesenbichler 2014; Friesenbichler, Böheim, and Laster 2014).

Structural change affected the sub-regions differently. Bucharest as the urban centre turned into a "re-construction city" (Pen and Hoogerbrugge 2012). Ilfov experienced a transformation away from agriculture (Ianoş, Cercleux and Pintilii 2010). The economic restructuring led to the emergence of a service based economy. In 2010, employment in manufacturing accounted for 20%, construction for 10% and services for approximately 70% of the economy, with ICT, telecommunication and finance as the largest industries (Pen and Hoogerbrugge 2012).

The emergence of this economic structure had massive socio-economic impacts on both areas, but especially on Ilfov. Its economic activities changed from subsistence farming as the starting point in the 1990s. The workforce was increasingly oriented toward the service sector, and the land was reclassified from agrarian to residential. This transformed large parts of Ilfov into suburbs of Bucharest. Hence, structural change not only required labour market adjustments, but also substantially altered the city's physical structure (Ianoş, Cercleux and Pintilii 2010).

Changes in the economic policy making were to a large degree driven by the European Union. Romania became an acceding country to the EU in 2004, and a full member in 2007. The EU membership facilitated economic openness and institutional reforms (Friesenbichler 2014), even though corruption remains an issue, and the creation of a metropolitan area is still in its infancy. A particular problem is the region's brain drain. While many employees have a university degree, employment opportunities are often slim and over-qualification is an issue. Hence, highly skilled people emigrate to other EU countries (Pen and Hoogerbrugge 2012). The derogation period on the free movement of labour for Romanians in the EU ended not before 2014 in many EU countries. One may therefore expect that the emigration of highly skilled labour to other EU countries will continue to be a problem.

The driver of change was the implementation of a better technology base. Foreign technologies were adapted, especially from EU-15 countries. This was made possible by incoming foreign direct investment. While this has driven the catching-up process of Romania as a whole, it was particularly pronounced in Bucharest, which is the country's foremost attractor-region of FDI. Between 2003 and 2006, Bucharest recorded approximately 60% of the country's total FDI (Pen and Hoogerbrugge 2012). The industries that were most prominently invested in were mainly food and drink in Ilfov county, and real estate and financial intermediation in the city of Bucharest (Ranga 2012). However, the strong linkages to the EU also imply that the region's economy depends on external economic developments. This not only holds due to its exposure to the business cycles of the EU and the need for foreign direct investment, but is also reflected by the regions reliance on structural funds (Pen and Hoogerbrugge 2012).

The structural change was both driven and accompanied by a change in the region's skills structure. Since the beginning of the transition, the human capital base has been constantly evolving and adjusting to market needs. Bucharest's labour market is characterised by a pool of well trained human capital. The majority of the employees have a university degree, and the wages of the work force are relatively low. However, there have been signs of a brain drain in recent years, with highly skilled people leaving Romania due to better job opportunities in other parts of the EU. This undermines the region's capacity to continue its structural change and upgrading the knowledge intensity of economic activities (Pen and Hoogerbrugge 2012).

To sum up Bucharest's experiences with industrial evolution, the region underwent a transition process from a command economy to a market based allocation system. This substantially transformed both the city and its rural surroundings. It successfully shifted the focus of economic activities to the service industry, and restructured existing industries. However, challenges remain, such as the building of trustworthy institutions that are able to continue implementing transition policies to maintain growth rates and address arising labour market mismatches and emerging brain drain issues.

*Antwerp*

The Antwerp province is the northernmost region of Belgium. It borders other Belgian provinces as well as the Netherlands in the North. The region has a high degree of urbanisation. It has a population density of 367 inhabitants per square kilometre, and its total population exceeds one million. The regional domestic product per capita of the Antwerp region amounted to 34,419 Euro, which was 14% above the Belgian average. Between 1990 and 2011, the regional per capita product in constant prices grew by 29% (base year: 2005). The regional economic growth rate hardly changed in the economic crisis. The yearly pre-crisis growth rate was on average +1.6% since 1990; the mean growth rate from 2009 onwards was 1.5%. The unemployment rate amounted to 6.2% in 2013, which is below the Belgium's national unemployment rate of 8.4% (see Table A.1).

Data on the service industry is only available for the later years in the sample, which is why long-run shifts in the sector composition cannot be shown. In 2007, manufacturing employed 27% of the workforce active in the private sector. Wholesale and retail trade accounted for 25%, construction for 10%, transport and communications for 12%, and hotels and restaurants for 6%. Real estate, renting and business activities made for a fifth of private sector employment. Within this sector, 91% were employed in the knowledge intensive business industries (even though only 1,387 people, or one percent of the sector's total employment, were in R&D).

The economy is dominated by several sectors. The city is home to one of Europe's largest ports, rendering transportation and shipment of goods key economic activities. Over and above the transport industry, the total employment in manufacturing and mining and quarrying changed from 103,100 in 1996 to 107,124 in 2007 (+3.4%). The industry concentration remained the same in the period from 1995 to 2007. Both years show a Herfindahl-index in manufacturing and mining and quarrying of 12.9%. In 1996 (earliest year available), the largest industry was the Manufacture of fabricated metal products, except machinery and equipment, making for 28.1% of the total employment in the manufacturing sector. Food and beverages accounted for 12.7%, and fabricated metal products for 9.4%. In 2007, the largest employer in the manufacturing sector was the manufacture of chemicals and chemical products industry, which made for 24.2% of the sector's total employment. Manufacture of food products and beverage accounted for 17.9%, and motor vehicles, trailers and semi-trailers for 13.2%. The average establishment size in chemicals and the car industry is substantially larger than in the food industry.

**Table A.4 Development of key manufacturing industries in Antwerp**

| Industry | Employment 1996 | Employment 2007 | Share 1996 | Share 2007 | Avg. Est. Size 1996 | Avg. Est. Size 2007 |
|---|---|---|---|---|---|---|
| DJ28;Manufacture of fabricated metal products, except machinery and equipment | 9661 | n.a. | 9.4% | n.a. | 92 | n.a. |
| DA15;Manufacture of food products and beverages | 13052 | 19133 | 12.7% | 17.9% | 76 | 15 |
| DG24;Manufacture of chemicals and chemical products | 28958 | 25925 | 28.1% | 24.2% | 397 | 153 |
| DM34;Manufacture of motor vehicles, trailers and semi-trailers | n.a. | 14132 | n.a. | 13.2% | n.a. | 124 |

*Source: Eurostat SBS data, WIFO calculations :*

The Regional Innovation Monitor does not provide information on the Antwerp region specifically, but on Flanders, the wider province, as a whole. In 2014, it classifies the region as an Innovation Follower. In 2004, it used to be an Innovation leader, i.e. the region fell back in its relative innovation performance. The Regional Innovation Scoreboard indicates that the gross expenditures on R&D were above both the national and the EU average. This was mainly driven by the private sector, even though governmental expenditures have increased from a very low level. Private sector R&D depends on a large share of foreign owned multinational enterprises with decision centres abroad.

The business sector is innovative, and human resources are well trained, with a large and growing share of the population in higher education. In 2012, the share of the population aged 25-64 with tertiary education attainment was 35.3%, which is poses a slight increase compared the 14.9%, the level in 2003 (Eurostat data). Also Flanders has a strong knowledge production system. The share of researchers in the active population, as well as the publication and impact rate of Flemish scientists are high. Also the patenting performance is above the EU-27 average, but not as high as the knowledge production would suggest. The major challenges identified in the Regional Innovation Monitor directly refer to the industry structure. While the region is a prominent attractor of foreign direct investment, it has yet failed to anchor R&D-activities of multinational enterprises in the regional innovation system. In addition, the report identifies the lopsided industrial structure and low degree of diversification as a possible challenge, as well as issues in the co-ordination of innovation governance institutions (Til 2012).

**Assessment of the industry evolution**

The regional economy is dominated by two industries – transportation due to the port of Antwerp and chemicals. Both industries are spatially concentrated around the port.

The port is the key element of the regional economy. While the Port Authority promotes intra-port competition (e.g., competition for land between terminals), the Port Authority seeks to integrate the supply chain, and provide common goods services such as the provision of information (Guardiola 2013). An Input-Output analysis using postcodes of the port's customers and suppliers shows that its activities are located in the province of Antwerp. This confirms the existence of agglomeration effects on one single transhipment location. Moreover, the region is well connected, and actors in the Antwerp province and the Brussels-Capital region are easily accessible by road, rail and inland waterway. Over and above logistics companies attached to the port, transport and trade are benefitting from the presence of the port, which acts as the shipper who delivers the goods that need to be transported. The port serves as a transport node to heavily industrialised countries of Europe, such as Belgium, the Netherlands, Germany and France (Coppens et al. 2007; Guardiola 2013).

In addition, a strong (petro-)chemical industry emerged, which supplies mostly to the Antwerp port actors. The chemical industry has grown to an impressive scale. The port's area is home to the largest chemical cluster in Europe, which is why Antwerp is sometimes referred to as the "Houston of Europe" (Coppens et al. 2007). Seven of the world's top ten (petro-) chemical companies are located in the cluster. The cluster itself is highly integrated, and diverse throughout the value chain. In 2014, the cluster comprises three refineries and four steam crackers that provide a stable local supply of raw materials. The port's infrastructure and connectedness enables them to obtain these over sea, by rail, barge and pipelines. These inputs are used in the production of chemical companies. All companies in the cluster collaborate on issues such as energy to minimise production costs.[68]

The Antwerp chemical cluster, like other European clusters, is well positioned in global chemical trade. However, these positions are under threat and many strong European clusters have lost employment and market position to Asia in recent years. While this affects the oil-supply and port-focused focused cluster of Antwerp to lesser degree, it is still relevant from a diversification point of view in the longer term. European chemical clusters are highly productive, but come with a legacy of assets which compete with facilities in Asia that can exploit potential scale economies and new technologies to a higher degree. This might lead to a consolidation phase of the chemical cluster landscape in Europe, which might also affect Antwerp. The European petrochemical industry as a whole has slowly moved from a model of within-company, process optimisation model to a cluster-based network architecture of co-located activities. This increased the flexibility of the industry, and has often been supported by policy makers by facilitating inter-firm collaboration or the provision of research and education facilities (Ketels 2007; van Wassenhove, Lebreton and Letizia 2007). In addition, complex regulations such as safety procedures are easier to implement if firms are located in geographical proximity (Reniers et al. 2009).

There is a lively policy debate about the diversification of the regional industrial structures. Its mature industries are under threat to lose market shares, which puts the current export performance at risk. The industrial structure seems very stable, which is perceived as a risk rather than an advantage, however. New industries have not emerged, and especially knowledge intensive sectors remained unchanged. This debate has also sparked a discussion about the role of human capital. While the region performs well in the education and research personnel indicators, there are reports of skills mismatches in some technology intensive sectors. The debate about structural change focuses on the establishment of a larger high-tech sector, for which brain-drain and brain-gain are topics. Brain-gain is hampered by the low remuneration of researchers as well as language restrictions. At the same time, there is a discussion about brain drain due to the higher mobility of researchers and highly skilled personnel (Til 2012).

A key question concerns the competitiveness of the current cluster structures. First, this refers to the port itself, which is exposed to competition between port infrastructures in Northern and Southern Europe as well as ports in Northern Europe. In addition the competitiveness of the port of Antwerp in comparison with other ports, the port performance will hinge on the trade performance of the firms that use the port (Guardiola 2013). Second, the key players of the chemical cluster will have to change its business model to implement decentralised structures. Although producers are very knowledgeable about the benefits of going beyond arm's length

[68] See https://chemicalparks.eu/sites/port-of-antwerp and http://www.portofantwerp.com/en/chemical-cluster; retrieved on 24th March 2015.

relationships with other firms, path dependence imposes practical limits to the fragmentation. For instance, frequent tendering practices with limited information sharing reduces planning visibility for service providers, which results in higher costs for producers (van Wassenhove, Lebreton and Letizia 2007). In recent years, there have been spillover effects from the chemical cluster to life science industries. Biotechnology typically relies on technology fields that are closely related to chemicals. However, these developments are still in their infancy, and the emergence of a larger industry is not yet ostensible.

To summarise the situation of Antwerp, the regional economy relies on the port, which is also home to a large chemical cluster that offers port-related services (e.g., plastics and oil). Like the port, the chemical firms are clustered geographically. However, they operate on a scale intensive business model. The industrial diversification toward other industries has hardly occurred, which has become a policy issue as both clusters increasingly face competition from other clusters (or transport nodes, respectively) from both overseas and within Europe.

### *Valencia*

The province of Valencia is an autonomous community located in the South-Eastern parts of the Spanish peninsula. It is one of Spain's 17 autonomous regions, and is divided into the provinces of Castellon, Valencia and Alicante. With a population of almost five million and 217 inhabitants per square kilometre, it is rather densely populated. In 2011, the regional domestic product amounted to 18,161 Euro, which was below the national average of 20,414. Between 1990 and 2011, the regional per capita product in constant prices grew by 22% (base year: 2005). The regional economic growth rate amounted to an average of +1.6% since 1990. Like other regions in Spain, also Valencia experienced a sharp decline in economic growth with the crisis. The mean growth rate between 2009 and 2011 was negative at -0.6%. The region faces severe labour market issues, with an unemployment rate of 28% and a youth unemployment rate of 53% (see Table A.1).

The sector wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods accounted for 29% of the private sector's total employment, manufacturing for 21% and construction for 20%. This high share mirrors the construction boom which became a structural issue in the later crisis. Hotels and restaurants made for 8% of the employment, showing the relevance of tourism to the region. Real estate, renting and business activities made for 6%. Within this sector, 27% made for real estate activities; knowledge intensive business services accounted for 64%.

Total employment in manufacturing and mining and quarrying increased from 210,022 in 1995 to 265,720 in 2007 (+26.5%). The employment-based Herfindahl-Index shows that industry concentration decreased from 10.4% to 9.9% in the same period. The largest industry of the region was the manufacture of other non-metallic mineral products. In 2007, its employment share was 18.9% (1995: 18.4%). Other main industries were the manufacture of fabricated metal products (12.6%) and the manufacture of furniture and other manufacturing (11.6%). This list indicates a structural change of the industry composition. In 1995, the industry tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear accounted for 14.6%, and the manufacture of textiles for 10.8%. Especially the decline in the employment share of textiles reflects structural issues of Spain as a whole at the regional level.

**Table A.5 Development of key manufacturing industries in Valencia**

| Industry | Employment 1995 | Employment 2007 | Share 1995 | Share 2007 | Avg. Est. Size 1995 | Avg. Est. Size 2007 |
|---|---|---|---|---|---|---|
| DJ28;Manufacture of fabricated metal products, except machinery and equipment | 22632 | 33368 | 10.8% | 12.6% | 9 | 8 |
| DB17;Manufacture of textiles | 22787 | 18873 | 10.8% | 7.1% | 16 | 10 |
| DC19;Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear | 30578 | 26566 | 14.6% | 10.0% | 11 | 9 |
| DI26;Manufacture of other non-metallic mineral products | 38705 | 50240 | 18.4% | 18.9% | 23 | 22 |
| DN36;Manufacture of furniture; manufacturing n.e.c. | n.a. | 30939 | n.a. | 11.6% | n.a. | 9 |

*Source: Eurostat SBS data, WIFO calculations*

The Regional Innovation Monitor classifies Valencia as a Moderate Innovator, and since 2004 its composite innovation index has been falling marginally. Compared to the European Union average, the Valencian Community shows relative strengths in aspects of innovation that are related to public funding, such as the share of graduates with tertiary education, lifelong learning, and public R&D expenditures. However, private sector activities perform poorly, which is mirrored by low employment shares in medium–high and high technology manufacturing and the services sector, or low private R&D expenditures. Innovation policies have tried to address these shortcomings, and set up a sector-oriented network of research centres whose main objective is to bring R&D to private companies. However, the poor cooperation culture persists. Firms are often reluctant to cooperate due to a perceived insufficient *appropriability* of innovation rents. Hence firms prefer to conduct R&D-efforts on their own (Etxaleku and Girbés 2011). In 2012, the share of the population aged 25-64 with tertiary education attainment was 30.1%, which lies significantly above the share of 2003 of 21.7% (Eurostat data).

**Assessment of the industry evolution**

Valencia is home to one of Spain's most important ports. Since 1985, the Port Authority has gradually expanded and developed the port's infrastructure. Maritime trade through Valencia has grown exponentially, increasing shipment volumes from 6.6 million tons in 1993 to more than 40 million tons in 2006. This attracted major shipping and transport companies, and facilitated the region's connectedness with global value chains (Prytherch and Boira Maiques 2009). However, the port activities generated little spin-offs, and the industrial structure of the region is still dominated by agriculture, in particular citrus, which continues to be a major source of income on the countryside. In addition, there is a long tradition in the manufacture of ceramic tiles and marble products, in which the region still maintains a competitive advantage.

Due to fierce international competition from Asia, the once prominent leather industry and the manufacture of textiles have been on decline since the end of the quota system of the multi-fibre agreements. In 1976, a car assembly plant of a major US car producer opened in a Almussafes in the Southern part of the province. In 2006, approximately 7,000 employees were employed at the plant. However, the site could not generate a cluster, and is exposed to fierce competition between production sites of the car manufacturing industry.

Tourism is another major source of income, with visitors coming mostly from the British Isles, Belgium, the Netherlands, Luxembourg, Germany and Scandinavian countries. The government of the city of Valencia planned to convert Valencia into a major destination for cultural entertainment tourism. This is most evident on lands east of the city, where the massive exhibition centre has been built – the Ciutat de les Arts i de les Ciències, where croplands and light manufacturing used to be (Prytherch and Boira Maiques 2009). However, tourism industry frequently reaches infrastructure boundaries in the summertime, especially when hydrological demand is high due to the higher population. In the pre-crisis period, the construction sector was a major driver of the economy (Zepeda et al. 2006).

Given the structural issues and the need for diversification, the region is searching for sources for diversification. For instance, tertiary education might provide a growth impulse that leads to industrial diversification. Valencia is home to several universities. However, these are not linked to regional development goals. On the one hand there would be the option to involve the tertiary education sector more strongly. Valencia's higher education institutions are highly autonomous from the central government, because they rely on the regional government for a large share of their funding. On the other hand, the higher education institutions do not operate in any way as a system, but rather as a set of independent institutions, each trying to respond to a wide range of needs and demands (Zepeda et al. 2006).

Human capital is generally regarded by policy documents as a means to promote structure change. For instance, the Regional Innovation Monitor highlights the need to improve the training of human resources to suit the needs of business and the knowledge society in general. This reflects wider issues, however, such as underdeveloped co-ordination mechanisms of training and education facilities, or low degrees of collaboration between the private sector and education (Etxaleku and Girbés 2011).

To sum up, Valencia is a region that is struggling with structural issues. While the port of Valencia, tourism and a relatively small manufacturing base generate some income, unemployment remains high and diversification into other sectors was hardly successful. This comes in spite of some attempts by policy makers to generate growth from within the region, e.g. by using tertiary education as an instigating factor.

*Bratislava*

The capital region of the Slovak Republic substantially expanded its economic activity. Its regional per capita product amounted to 8,109 Euro in 1990. By 2011, this figure increased to 22,707 Euro. This equates to a growth rate in the regional per capita product in constant prices of 180% (base year: 2005), which generated a per capita income that is higher than the Southern European province of Valencia of the present analysis. The Bratislava region is the economic centre of the country – its regional per capita income was more than five times the national average in 2011. The catching-up process is still ongoing. The average annual growth figures decreased only slightly from +5.4% before the economic crisis in the period from 1990 to 2008 to +4.1% between 2009 and 2011. At 6.4%, the unemployment rate is rather low, even though the youth unemployment rate of 19.7% points at labour market issues. The region makes for the bulk of economic activity in the Slovak Republic. With a population density of 297 inhabitants per square kilometre, the region has a high level of urbanisation. While only 11% of the country's population live in the region, its per capita product is more than twice the national average. The unemployment rates in the region are approximately half of the national average rates (see Table A.1).

The industry composition changed significantly between 1995 and 2007. In 1995, transport storage and communication accounted for the largest employment share in the private sector (36%), which decreased by 2007 to 22%. Also manufacturing declined from 24% to 19%, and electricity, gas and water supply from 11% to 2%. The share of real estate, renting and business activities increased from 9% in 1995 to 24% in 2007 (knowledge intensive businesses made for 88% of this subsector). Also wholesale and retail trade expanded from 8% to 23% in the same period. The employment share of hotels and restaurants remained stagnant; it accounted for 3% in 1995 and 2% in 2007.

Total employment in manufacturing and mining and quarrying slightly increased from 29,333 in 1995 to 31,643 in 2007 (+7.9%). In the same period, the industry concentration decreases slightly. In 1995, the employment based Herfindahl-index was 12.6%. In 2007, this value was 10.6%. In 2007, the largest industry was publishing, printing and reproduction of recorded media with an employment share of 16.8%. Machinery and equipment accounted for 14.3% and the manufacture of other non-metallic mineral products for 14%. This resembles the key industries of 1995, where machinery and equipment made for an employment share of 18.2%, followed by electrical machinery (18%) and other non-metallic mineral products (14.9%).

**Table A.6 Development of key manufacturing industries in Bratislava**

| Industry | Employment 1995 | Employment 2007 | Share 1995 | Share 2007 | Avg. Est. Size 1995 | Avg. Est. Size 2007 |
|---|---|---|---|---|---|---|
| DA15;Manufacture of food products and beverages | n.a. | 3599 | n.a. | 11.3% | n.a. | 43 |
| DG24;Manufacture of chemicals and chemical products | 3665 | 1231 | 12.5% | 3.9% | n.a. | 21 |
| DI26;Manufacture of other non-metallic mineral products | 4361 | 4444 | 14.9% | 14.0% | n.a. | 48 |
| DL31;Manufacture of electrical machinery and apparatus n.e.c. | 5269 | 2827 | 18.0% | 8.9% | n.a. | 33 |
| DK29;Manufacture of machinery and equipment n.e.c. | 5340 | 4558 | 18.2% | 14.3% | n.a. | 23 |
| DE22;Publishing, printing and reproduction of recorded media | n.a. | 5331 | n.a. | 16.8% | n.a | 12 |

*Source: Eurostat SBS data, WIFO calculations*

The Regional Innovation Monitor suggests an improvement of the regional innovation capacities. In 2004, the region was classified as a Moderate Innovator, while from 2010 onwards it has been assigned to the cluster of Innovation Followers. The biggest challenge is the region's dual economy, which is a phenomenon that is observable in many catching-up countries. That is, there are internationally active firms that are often foreign owned on the one hand. On the other hand, there are typically local SMEs that exhibit low productivity levels and compete at low production cost. While many multinational enterprises are active in the regions, they do not conduct research and development in Bratislava and show little interest in co-operating with local universities and research institutions. Nevertheless, Bratislava's economic power compared to other Slovak regions is also reflected in the Regional Innovation Scoreboard 2009, which ranks the Bratislava region highest in innovation indicators among Slovak regions. Its average composite score 0.45, which is close to the EU average of 0.46. The innovation indicators mirror the FDI-driven catching-up process. Technology transfer mainly occurred by the multinational companies, which is the dominant type of innovation. Science or research-driven innovations are less important. It scored well in indicators such as non-R&D innovation expenditures, employment in knowledge intensive services and life-long learning. Challenges were identified in broadband access, the number of EPO patents, business R&D expenditure and the shares of SMEs that innovate innovating in-house (Baláž 2011). In 2012, the share of the population aged 25-64 with tertiary education attainment was 37.4%, which is substantially higher than the share in 2003 of 26.1% (Eurostat data).

**Assessment of the industry evolution**

Like other transition economies, the economy of the Bratislava region underwent the structural adjustments that the systemic change from a command economy to a private sector driven allocation required (Altzinger and Maier 1996; Friesenbichler, Böheim, and Laster 2014). After initial macro-economic adjustments, the region exhibited an impressive catching-up performance. Its geographical location granted the Bratislava region an advantage in the growth process that began in the mid 1990s. The region borders with Vienna, Austria, and thereby constitutes the Bratislava-Vienna corridor. The economic centres of Austria and Slovakia are within commuting distance of each other. Geographical proximity facilitated foreign direct investment, which accelerated Bratislava's catching up, and allowed the region to achieve near full employment. The border-crossing agglomeration is fully competitive against other large urban regions. The transition process fundamentally changed the industry structure. Between 1995 and 2004 the intensity of structural change was approximately 50% higher than in other EU-countries. Especially the finance and insurance industry made for a larger share than the EU average would suggest. However, the wage-gap within the region remains high, which mirrors productivity-gaps so that cost competition does not much impair an interregional division of labour, a pre-condition for economic integration. Structural change in both parts of the twin-city is producing further disengagement of regional specialisation (Altzinger and Maier 1996; Mayerhofer, Fritz and Platsch 2007).

Approximately two thirds of total foreign investments of the Slovak Republic are being made in Bratislava. The low tax rate has attracted multinational enterprises, which located their headquarters in Bratislava (Bednar, Danke and Grebenicek 2013). In addition, service (esp. IT and consulting) and manufacturing companies have invested in the region. The automobile industry set up assembly lines, and large machinery and equipment companies invested in production facilities. In 2014, more than three quarters of total employment is in the service sector, mainly composed of trade, banking, IT, telecommunication as well as tourism.

In recent years, there have been grassroots developments in the creative industries (Power 2011). This sector consists of art and culture (e.g., entertainment and museums), cultural (e.g., publishing, broadcasting, sound recording) and creative industries (e.g., architecture, software). In 2011 employed approximately 20,000 people in the region (Bednar, Danke and Grebenicek 2013).

However, challenges to the regional development remain. One is to maintain the attractiveness of foreign-direct investment under increasing wages. The region will have to continue to attract FDI despite increasing wages. This requires investments to contain more knowledge, which also might imply that technologies are more difficult to imitate, thereby foreclosing international competition between investment locations. In addition, most research is conducted as basic research, which is also the policy field. Applied research and linkages between firms and research facilities is under-developed (Baláž 2011). A technological upgrading would, along with institutional reforms and infrastructure investments, facilitate the continued integration with the Vienna region (Mayerhofer, Fritz and Platsch 2007).

The extent of technological upgrading will have to be accompanied by adjustments of the skill base that the regional economy can draw on. In the medium run, the wage level is expected to rise, which may undermine the cost-advantage of local SMEs. This may encompass opening the education system to a wider population; current policies aim at an elitist university education and high quality research. On the one hand, this seems to have facilitated the generation of a highly professional workforce from which sophisticated could benefit. On the other hand, this might have hampered the upgrading of the parts of the human capital that the less productive SME base can access, which again seems to have held back the development of absorptive capacities Baláž 2011.

To summarise, Bratislava is a region that benefitted from its proximity to Vienna. In the economic transition, it successfully established a diverse firm base with a strong service sector. After overcoming the legacy of a command-economy and the establishment of a trade sector, especially knowledge intensive business sector grew. However, a dual economy remains, i.e. there are both highly productive firms and local firms that – in comparison – perform rather poorly. Challenges such as the technological upgrading and a continued integration with the Vienna region (e.g., by institutional reform) remain.

## Discussion and Summary

This section developed case study evidence for five regions in the European Union. These were identified by a stepwise selection process using all NUTS2 regions in the EU as the sampling universe. The selection criteria considered a sufficient geographical coverage and regional innovation capabilities, a region's size (small regions were not considered) and carbon leakage and energy intensity as proxies for scale economies. The regions chosen were Antwerp (Belgium), Valencia (Spain), Bratislava (Slovak Republic) Styria (Austria), and Bucharest (Romania).

The case studies revealed different development patterns. Some regions faced severe structural challenges. For instance, Bratislava and Bucharest were challenged to establish a market economy after the collapse of communism. Styria's metal industry, the region's formerly dominant sector, was confronted with a structural crisis in the 1970s and 1980s. In the meantime, the challenged sectors of all three regions have restructured, which was accompanied by a diversification process, especially toward more knowledge intensive business services. Also Antwerp is challenged to maintain its competitiveness in its energy-intensive key sectors such as transport and chemicals. Valencia had to compensate for the declining textile and leather industry. In Antwerp and Valencia, the economic diversification performance seems to be less dynamic. This indicates that once established comparative advantages tend to be persistent over time.

The data availability is poor for the service sector, which challenges a comprehensive analysis of the structural evolution of the regional economies. Nonetheless, more detailed, long-run employment information is available for Styria and Bratislava. In both regions, the manufacturing share declined substantially, even though total employment remained rather stable in absolute numbers. The declining manufacturing share was accompanied by an increase in the employment share of knowledge intensive business services. For Styria, not only employment information is available, but also data on the number of establishments. This indicates a significant deepening of this subsector. It seems that activities that used to be conducted in manufacturing have shifted to specialised segments of the service sector. Related variety seems to have particularly increased in knowledge intensive business services.

One can interpret industrial dynamics from a "varieties of capitalism" perspective. The regions located in the EU-15 countries Austria, Spain and Belgium can be classified as coordinated market economies, where existing actors and institutions interact strategically to channel and direct allocation processes. On the other hand, EU-13 countries do not have that degree of coordination among actors due to their past as command, and then transition economies. Hence, they are required to rely on a more market based economy. This viewpoint corroborates the notion that the catching-up process of the EU-13 countries was driven by the emergence of new industries, thereby increasing the economies' unrelated variety.

The evolution of the diversification pattern differs across regions. The diversification of Bratislava and Bucharest, which occurred through a catching-up process, increased these economies' unrelated variety. New manufacturing industries emerged that were not considered by the command economy that collapsed with the end of the communist regimes. In addition, the once underdeveloped service industry flourished and turned into a driver for economic growth. These results mirror the diversification pattern established in the econometric analysis from above. In the EU-15 Member States, diversification occurred after a deepening of industries and an increase in the related variety, within the boundaries of related technology fields. For instance, Styria diversified after the restructuring of the steel industry into both machinery and equipment and the relatively new automobile industry. Antwerp used the port structures to diversify. Ancillary services such as oil led to the establishment of a chemicals industry, which later evolved into a small life science sector.

Another question concerns the origins of the impetus to diversify. In Bratislava and Bucharest, industrial diversification was predominantly driven by foreign direct investment, which served as a vehicle of technology transfer. While other inputs (e.g., education, infrastructure) were necessary to maintain economic growth, the growth impetus was investment by firms from other countries in the European Union. However, policy documents in both regions reflect concerns to maintain growth rates, which may require a diversification process beyond the outsourcing destination of international value chains. In the regions in EU-13 countries, industrial diversification was by and large a generic process that was mainly driven by regional industrial policies. This is plausible if one assumes that rents from FDI spillovers decrease with regional capacities. Also diversification into relatively unrelated industries, like in Styria, occurred to a substantial degree via foreign direct investment at a time when Styria's economic capabilities were lower than today's. More generally, trade and global value chains are linked with diversification performance. Regions whose industrial structures are well diversified tend to be embedded in global value chains and partake in the international division of labour, respectively.

The case studies also shed light on industrial rejuvenation processes. In Styria, Bucharest and Bratislava, the initial base was challenged by inefficiencies linked to public ownership, which were eventually overcome by the fragmentation and decentralisation of troubled firms and industries. The number of firms increased, and the average establishment size decreased. This indicates a deepening of the industry structure and an increase in related variety. This “industrial rejuvenation” seems to have been essential for the survival of the troubled industries.

The fragmentation of the industrial structure facilitated the restructuring of the regional technology base. If a key industry in a region faced structural challenges (e.g., due to a negative demand shock), it was required to re-structure. This implies not only that workforce is set free, but also that capabilities are lost. The abandonment of technologies tends not to occur at the “technological core” of a region, but at its margins. Restructuring the knowledge base typically implies larger frictions in integrated, large corporations than in a network of smaller firms, in which firms with inefficient, not competitive technologies may exit. At the same time, activities seem to have shifted away from the manufacturing sector to knowledge intensive service industries. This was especially the case in Styria and Bratislava.

The share of trade- and energy-intensive industries at significant risk of carbon leakage varies. If interpreted as a proxy for economies of scale and high fixed costs, one may argue that higher leakage indicators reflect a higher degree of industrialisation. This implies that regions with high shares of carbon-leakage affected industries are more exposed to structural shocks due to their relative inflexibility to adjust supply. The data show that especially Styria and Antwerp are regions with high carbon leakage and energy intensity indices. Especially Antwerp’s industrial structure was found to be specialised in industries classified as energy intensive. In other words, economic activity is centred around potentially carbon-leakage and energy-intensive industries, with few other economic activities in the region. The indicators for the regions in the EU-13 countries are lower, which might be explained by the transition process that led to closures of inefficient plants and the implementation of state-of-the-art production technologies.

Eventually, escaping path dependence has shown to be difficult, and the formation of human capital was often named as a potential instrument to foster a diversification process. Valencia and Antwerp struggle to instigate both growth and industry diversification. Especially, the provision of higher education, often cited as a growth-driver from endogenous growth theory, seems to have been a necessary input for diversification. However, increasing the share of college and university graduates alone has shown to be insufficient. Also regions that struggle to achieve industrial diversification may perform well in education indicators. The regions in which structural change occurred to a substantial degree have shown to continuously adjust the required human capital base to achieve a relatively efficient skills matching on the labour market. This may be reflected in higher shares of tertiary educated people, but increasing the shares alone seems to be insufficient to generate growth and diversification processes. The case studies rather indicate that the human capital base needs to co-evolve with a region’s technological base and firms’ absorptive capacities.

A technological frontier argument became evident, too. Regions that are technologically more advanced seek to promote research and development and establish an environment conducive to firms or networks of firms that potentially produce innovations “new to the world” (e.g., Styria). Regions like Bratislava, which is still in a catching up process, seek to foster a more encompassing business environment. For instance, a more widely available skill-base may facilitate overcoming the lopsided productivity structure in which less productive firms have poor access to adequately skilled human capital. Both Bratislava and (to a smaller extent) Bucharest seem to be at a switching point, where an FDI driven catching-up process is required to turn into a growth process driven by more innovation and domestic investment.

In addition, there is some evidence with regard to specific industries. The case studies indicate a shift away from manufacturing towards services. Many of the emerging firms in the service sector are linked to manufacturing, however. Regions with a strong manufacturing base also show a strong subsector of knowledge intensive business services (e.g., Styria, Bratislava). Another finding indicates that urban areas like Bratislava or Valencia seem to have developed knowledge-intensive, creative industries. However, a skilled workforce and the presence of universities alone do not generate growth or diversification, which is illustrated by Valencia’s experiences.

## A.2. Excursus – Energy Intensive Industries

In this section, the econometric analyses presented in the report are extended taking into account the role of energy intensive industries. It analyses whether the investigated specialisation patterns are different if industries are energy intensive (or exposed to a significant risk of carbon leakage). Finally, the section investigates whether high shares of energy intensive industries affect the role of related and unrelated variety for economic performance. The analysis follows the definition of a list of sectors and subsectors which are deemed to be exposed to a significant risk of carbon leakage set by the European Commission (see Box A.). The main focus in this section relies on the energy intensive industries classified there.

**Box A.2 Industries exposed to a significant risk of carbon leakage**

The analyses follows the definition of a list of sectors and subsectors which are deemed to be exposed to a significant risk of carbon leakage set by the European Commission in accordance with the rules set out in Directive 2003/87/EC as follows.

Article 10a(15) of Directive 2003/87/EC

A sector or subsector shall be deemed to be exposed to a significant risk of carbon leakage if

a) the sum of direct and indirect additional costs induced by the implementation of this Directive would lead to a substantial increase of production costs, calculated as a proportion of the gross value added, of at least 5 %; and
b) the intensity of trade with third countries, defined as the ratio between the total value of exports to third countries plus the value of imports from third countries and the total market size for the Community (annual turnover plus total imports from third countries), is above10 %.

Article 10a(16) of Directive 2003/87/EC

Notwithstanding paragraph 15, a sector or subsector is also deemed to be exposed to a significant risk of carbon leakage if

a) the sum of direct and indirect additional costs induced by the implementation of this Directive would lead to a particularly high increase of production costs, calculated as a proportion of the gross value added, of at least 30 %; or
b) the intensity of trade with third countries, defined as the ratio between the total value of exports to third countries plus the value of imports from third countries and the total market size for the Community (annual turnover plus total imports from third countries), is above 30 %.

Article 10a(17) of Directive 2003/87/EC

The list referred to in paragraph 13 may be supplemented after completion of a qualitative assessment, taking into account, where the relevant data are available, the following criteria:

a) the extent to which it is possible for individual installations in the sector or subsector concerned to reduce emission levels or electricity consumption, including, as appropriate, the increase in production costs that the related investment may entail, for instance on the basis of the most efficient techniques;
b) current and projected market characteristics, including when trade exposure or direct and indirect cost increase rates are close to one of the thresholds mentioned in paragraph 16;
c) profit margins as a potential indicator of long-run investment or relocation decisions.

Pursuant to Directive 2003/87/EC the criteria defined above (except Article 10a(17)) have been renamed in Directive 2014/746/EU as follows:

- A: criterion set out in Article 10a(15) of Directive 2003/87/EC
- B: criterion set out in Article 10a(16)(a) of Directive 2003/87/EC
- C: criterion set out in Article 10a(16)(b) of Directive 2003/87/EC

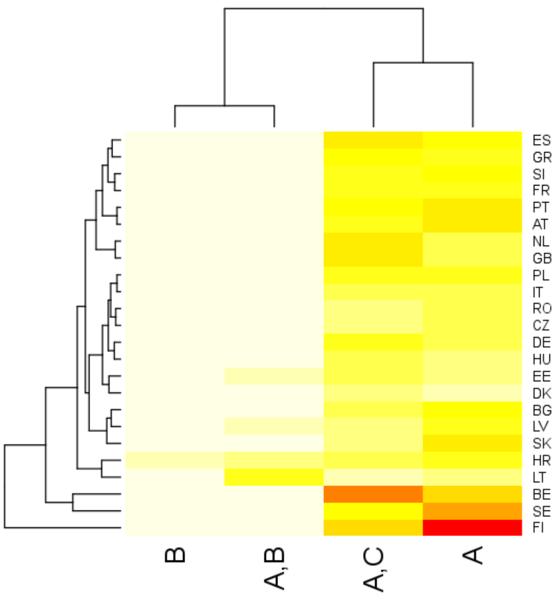
A complete list of industries fulfilling the criteria above are shown in Table A.19.

As defined above, the list of industries exposed to carbon leakage includes both energy intensive and trade intensive industries. In particular, the definition set in Article 10a(16)b focuses on the latter type of industries. In order to verify the distinction between specialisation patterns stemming from energy intensive industries and trade intensive industries the analyses is amended by trying different alternative classification schemes (e.g. following Ecorys 2009) but also a new calculated classification based on ETS firm level data in order to come up with an assignment of products or industries as energy intensive at a less aggregated level than NACE Rev. 2 3-digit industries.

## Patterns of specialisation in energy intensive industries across the EU-28 countries

The EU-28 countries are characterised by heterogeneous patterns with regard to energy intensive industries. Figure A.2 is a so-called heat plot which is a matrix in which each cell represents a country-industry pair. The colour represents the underlying shares of energy intensive industries in total exports. Dark colours present high indicator values (in the case of Figure A.3 high shares of energy intensive industries in total exports) whereas light colours represent low indicator values. The data have been clustered using a hierarchical cluster algorithm in the two dimensions of the matrix (by country and by sector), and the tree structure on top and the side of the matrix represents the dendrogram for this clustering exercise. In this dendrogram the branches that lie close together indicate high statistical correlation between the adjacent observations. The result is a matrix in which it is possible to identify patterns of specialisation across industries and countries. A first glance at the importance of energy intensive industries in total exports reveals that within the EU Belgium (BE), Sweden (SE) and Finland (FI) have high shares of energy intensive products in their export portfolios (see Figure A.2). This holds for Finland and Sweden in particular for industries classified as Type-A (for a detailed list of these industries see Table A.19), for Belgium for industries classified as both Types A and C. Furthermore, Croatia (HR) and the Baltic countries Estonia (EE), Latvia (LV) and Lithuania (LT) have comparably high shares in energy intensive industries for which both energy intensive criterias (A and B) apply. According to the cluster analysis, within the group of countries with comparably high shares of energy intensive industries Sweden and Belgium show similar patterns in their energy intensive industry portfolio. Similarly Croatia and Lithuania are also identified as being similar.

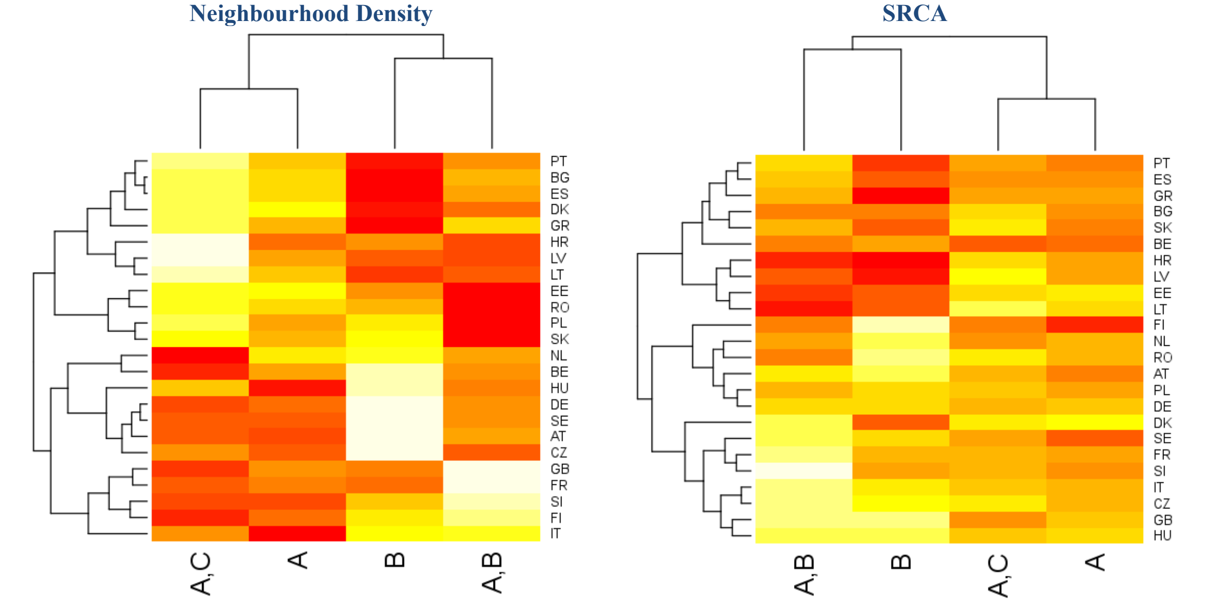
**Figure A.2 EU-28 countries clustered by the share of energy intensive industries in total exports**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

Figure A.3 presents the weighted industry values for product relatedness (product neighbourhood density) in the left panel and the standardised revealed comparative advantages (srca) in the right panel for the energy intensive industries (as defined in Box A.) across the EU-28 countries. The left panel of Figure A.3 shows clear clustering patterns. At the bottom of the panel, about half of the EU member states show high product relatedness in the industries that fulfil the criteria both A and C or A according to the carbon leakage definition. At the top, the other half of EU countries has high product relatedness in industries classified as both A and B or B. Interestingly, each group is characterisied in comparably low levels of product relatedness in energy intensive industries the respective other group has high levels of relatedness in. When looking at specialisation measured in terms of standardised RCA values, it turns out that only the second group is specialised in energy intensive industries. The first group of countries has existing capabilities related to energy intensive industries but their current degree of specialisation therein is low. Figure A.2 and Figure A.3 therefore show that the EU-28 countries are heterogenous regarding their specialisation in energy intensive industries.

**Figure A.3 Specialisation patterns across energy intensive industries and countries: Clustering based on product relatedness (left) and SRCA (right)**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

## Energy intensive industries, specialization and diversification

Econometrically investigating specialisation patterns in energy intensive industries clearly shows that EU Member States are less specialised in energy intensive industries than non-EU countries. The dummy indicating whether an industry is energy intensive or not is significantly negative (see TableA.7). The same holds for world market shares. The EU countries have on average lower market shares in energy intensive industries when compared with non-EU countries. On the other hand, the opposite pattern is observed when including those product classes that are produced by industries of the carbon leakage list classified as trade intensive. The EU countries are overall more specialised in industries that are potentially affected by carbon leakage.

In the short run, however, gaining world market shares in products less related to the country's local capabilities is easier if the product is produced in energy intensive industries. The interaction effect between neighbourhood density and the dummy for energy intensive industries on world market shares is negative. On the other hand, when explaining standardised RCA values the respective coefficient is insignificant. For developing new or improving existing comparative advantage, energy intensity does not seem to affect the importance of relatedness when explaining specialisation patterns. However, looking at alternative definitions of energy intensive industries, the empirical evidence is more clear-cut. Developing new comparative advantage in energy intensive industries is less dependent on the existence of related capabilities. This result indicates that other factors (e.g. energy prices) might dominate the role of local capabilities when explaining specialization patterns. In the long run, the significantly positive interaction term reduces the sluggishness effect of relatedness. Energy intensive industries are more likely to export products that are more closely related to the country's product space.

On the other hand, the more trade intensive (i.e. the higher the importance of international trade in a product market) a product, the more important it is for a country in the long run that the product is close to the country's product space in order to remain competitive (see de Waldemar and Poncet 2013, for a similar result). Redoing the analysis using dummies for products that are exposed to significant risk of carbon leakage[69] (for details of the definition see Box A.) delivers positive interaction effects with neighbourhood density on world market shares (see Table A.8 in appendix). As described above, the long-run interaction effect is insignificant for energy intensive industries. The results clearly show that the pattern observed for the carbon leakage industries stems from the dominance of trade intensive industries. Using alternative classification schemes for energy intensive industries support this finding (results not reported).

[69] See e.g. Gerlagh and Kuik (2007) or Di Maria and Van der Werf (2008) for theoretical considerations about international technology spillovers on carbon leakage.

**TableA.7 Specialisation, product space and energy intensity, product level regressions, EU-28 countries, dependent variable = standardised revealed comparative advantage (srca) or world market shares (wms)**

| | Standardised revealed comparative advantage, srca | | | | World market share, wms | | | |
|---|---|---|---|---|---|---|---|---|
| | | QML Flogit Estimator | | | | QML Flogit Estimator | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| | APE | Sign | Sign | Sign | APE | Sign | Sign | Sign |
| **EU-28 countries** | (p-value) | | | | (p-value) | | | |
| Lagged dependent variable, (L.srca or L.wms) | 0.504*** | +++ | +++ | +++ | 0.091*** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Dep.Variable time t=0, (srcat=0 or wmst=0) | 0.101*** | +++ | +++ | +++ | 0.020*** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 1.471*** | +++ | +++ | +++ | 0.112*** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -0.836*** | --- | --- | --- | 0.019*** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication, soph | 0.004*** | +++ | +++ | +++ | -0.000** | -- | -- | 0 |
| | (0.000) | | | | (0.016) | | | |
| Product sophistication (LR), soph_mean | -0.002*** | --- | --- | --- | -0.000 | 0 | 0 | - |
| | (0.000) | | | | (0.159) | | | |
| Energy intensity, eii_ab | -0.016*** | --- | --- | --- | -0.000*** | +++ | +++ | --- |
| | (0.000) | | | | (0.000) | | | |
| Interaction Neighb.density x Energy intensity | | 0 | 0 | | | --- | --- | |
| Interaction Neighb.density x Energy intensity (LR) | | +++ | +++ | | | 0 | 0 | |
| Interaction Prod. Soph. x Energy intensity | | --- | | --- | | 0 | | 0 |
| Interaction Prod. Soph. x Energy intensity (LR) | | --- | | --- | | 0 | | 0 |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 |
| Pseudo $R^2$ | 0.818 | 0.818 | 0.818 | 0.818 | 0.796 | 0.796 | 0.796 | 0.796 |
| Deviance | 141387 | 141126 | 141207 | 141305 | 9784 | 9776 | 9776 | 9783 |
| Log Pseudolikelihood | -373958 | -373827 | -373868 | -373917 | -55233 | -55229 | -55230 | -55233 |
| Wald-Test (Time Dummies) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Wald-Test (Country Dummies) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*

*Source: WIFO calculations*

**Table A.8 Specialisation, product space and carbon leakage, product level regressions, EU-28 countries, dependent variable = standardised revealed comparative advantage (srca) or world market shares (wms)**

| | Standardised revealed comparative advantage, srca | | | | World market share, wms | | | |
|---|---|---|---|---|---|---|---|---|
| | | QML Flogit Estimator | | | | QML Flogit Estimator | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| | APE | Sign | Sign | Sign | APE | Sign | Sign | Sign |
| **EU28 countries** | (p-value) | | | | (p-value) | | | |
| Lagged standardised revealed comparative advantage L.srca | 0.505 *** | +++ | +++ | +++ | 0.091 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.101 *** | +++ | +++ | +++ | 0.020 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 1.478 *** | +++ | +++ | +++ | 0.112 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -0.838 *** | --- | --- | --- | 0.019 *** | 0 | 0 | +++ |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication, soph | 0.004 *** | +++ | +++ | +++ | -0.000 ** | 0 | -- | 0 |
| | (0.000) | | | | (0.015) | | | |
| Product sophistication (LR), soph_mean | -0.004 *** | --- | --- | --- | -0.000 ** | 0 | - | 0 |
| | (0.000) | | | | (0.060) | | | |
| Carbon leakage (dummy) | 0.009 *** | +++ | +++ | +++ | 0.000 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Interaction Neighb.density x Carbon leakage | | --- | --- | | | --- | --- | |
| Interaction Neighb.density x Carbon leakage (LR) | | +++ | +++ | | | +++ | +++ | |
| Interaction Prod. Soph. x Carbon leakage | | --- | | --- | | 0 | | -- |
| Interaction Prod. Soph. x Carbon leakage (LR) | | 0 | | 0 | | --- | | 0 |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 |
| Pseudo $R^2$ | 0.818 | 0.818 | 0.818 | 0.818 | 0.796 | 0.797 | 0.797 | 0.796 |
| Deviance | 141518 | 141426 | 141454 | 141488 | 9785 | 9758 | 9763 | 9779 |
| Log Pseudolikelihood | -374023 | -373977 | -373991 | -374008 | -55234 | -55220 | -55223 | -55231 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*

*Source: WIFO calculations*

Interestingly, when investigating the effects whether industries are potentially exposed to carbon leakage at the regional level, the opposite sign for the relationship with RCA values appears when comparing with the country level (see Table A.10 in the appendix). The result hints at lower degrees of specialisation of EU regions in industries potentially affected by carbon leakage. However, the deviation from the results observed at the country level is easily explained by the differences in the data used. At the country level, product level trade data are available (incl. extra-EU trade) while the regional analysis is stuck to explaining industrial specialisation within Europe. As explained in chapter 3, the positive sign for the carbon leakage dummy is mainly driven by the inclusion of trade intensive products in the list of carbon leakage affected industries. When looking at specialisation patterns of productive structures within the EU the importance of the trade intensive industries is lower and their effect is superimposed by pure energy intensive industries. For the latter completely the same patterns appear as for the country level. EU regions are on average less specialised in industries the more energy intensive they are.

**Table A.9 Specialisation, product space and energy intensity, Regional level regressions, NUTS2 regions, dependent variable = standardised revealed comparative advantage (srca)**

| | Standardised revealed comparative advantage, srca | | | | |
|---|---|---|---|---|---|
| | QML Flogit Estimator | | | | |
| | (1) | | (2) | (3) | (4) |
| **EU28 countries** | APE (p-value) | | Sign | Sign | Sign |
| Lagged dependent variable, (L.srca) | 0.590 (0.000) | *** | +++ | +++ | +++ |
| Dep.Variable time t=0, (srcat=0) | 0.086 (0.000) | *** | +++ | +++ | +++ |
| Neighbourhood density, empdens | 0.103 (0.000) | *** | +++ | +++ | +++ |
| Neighbourhood density (LR), empdens_mean | -0.008 (0.684) | | 0 | 0 | 0 |
| Product sophistication, soph | -0.001 (0.534) | | 0 | 0 | 0 |
| Product sophistication (LR), soph_mean | 0.005 (0.002) | *** | +++ | +++ | +++ |
| Energy intensity, eii_cl_ab | -0.013 (0.000) | *** | --- | --- | --- |
| Interaction Neighb.density x Energy intensity | | | 0 | | 0 |
| Interaction Neighb.density x Energy intensity (LR) | | | 0 | | 0 |
| Interaction Prod. Soph. x Energy intensity | | | | ++ | ++ |
| Interaction Prod. Soph. x Energy intensity (LR) | | | | 0 | 0 |
| Time Dummies | YES | | YES | YES | YES |
| Country Dummies | YES | | YES | YES | YES |
| Number of observations | 212,654 | | 212,654 | 212,654 | 212,654 |
| Pseudo $R^2$ | 0.938 | | 0.938 | 0.938 | 0.938 |
| Deviance | 11434 | | 11434 | 11422 | 11422 |
| Log Pseudolikelihood | -50650 | | -50649 | -50644 | -50643 |
| Wald-Test (Time Dummies) | 0.001 | | 0.001 | 0.001 | 0.001 |
| Wald-Test (Country Dummies) | 0.000 | | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

When looking at the effect of product sophistication on world market shares, the patterns for energy intensive industries are less clear cut. Trying different approaches of classifying energy intensive industries delivers different results. The interaction effects using the carbon leakage definition of energy intensive industries (types A & B) delivers insignificant results. For alternative definitions tested, if significant effects occur they are negative both in the short run and the long run hinting at lower average world market shares for more energy intensive products.

Specialising in more sophisticated products seems to be even more difficult for EU Member States than gaining world market shares if the products are energy intensive. Both the short-run and the long-run interaction effects are negative. In the short run, the comparative advantage of the EU's higher quality through innovation allowing to specialise into more sophisticated products seems to be reduced by disadvantages in energy prices. In the long run, this disadvantage in energy prices reinforces the general difficulties (i.e. the higher capabilities required) of specialising in more sophisticated products.

On the contrary, world market shares seem to be less concentrated if more sophisticated products are more trade intensive as defined in the carbon leakage list. Interaction terms between the dummy for the carbon leakage affected industries and product sophistication are negative but not always significant (depending on the specification of the regression). Product sophistication itself is not significantly deviating from zero. This result is not surprising taking into account that the carbon leakage list includes a broad range of trade intensive industries. If an industry is trade intensive it might be assumed that more countries are exporting these products. Exports of less trade intensive industries are more concentrated in fewer countries and therefore the world market shares are on average higher.

**Table A.10 Specialisation, product space and carbon leakage, Regional level regressions, NUTS2 regions, dependent variable = standardised revealed comparative advantage (srca)**

| | NUTS2 regions | | | |
|---|---|---|---|---|
| | | QML Flogit Estimator | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | | | |
| Lagged standardised revealed comparative advantage L.srca | 0.589 *** (0.000) | +++ | +++ | +++ |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.087 *** (0.000) | +++ | +++ | +++ |
| Neighbourhood density, dens | 0.103 *** (0.000) | +++ | +++ | +++ |
| Neighbourhood density (LR), dens_mean | -0.010 (0.583) | 0 | 0 | 0 |
| Product sophistication, soph | -0.001 (0.404) | 0 | 0 | 0 |
| Product sophistication (LR), soph_mean | 0.006 *** (0.000) | +++ | + | + |
| Carbon Leakage; eii_cl | -0.008 *** (0.000) | --- | --- | --- |
| Interaction Neighb.density x Carbon Leakage | | + | | 0 |
| Interaction Neighb.density x Carbon Leakage (LR) | | 0 | | 0 |
| Interaction Prod. Soph. x Carbon Leakage | | | 0 | 0 |
| Interaction Prod. Soph. x Carbon Leakage (LR) | | | 0 | 0 |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |
| Regional Control Variables | YES | YES | YES | YES |
| Number of observations | 212,719 | 212,719 | 212,719 | 212,719 |
| Pseudo $R^2$ | 0.938 | 0.938 | 0.938 | 0.938 |
| Deviance | 11464 | 11461 | 11461 | 11457 |
| Log Pseudolikelihood | -50680 | -50678 | -50679 | -50677 |
| Wald-Test (Time Dummies) | 0.001 | 0.001 | 0.001 | 0.001 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively; ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

Furthermore, investigating whether the importance of neighbourhood density for specialisation varies depending on the industries classified as affected by energy intensity or not, the evidence is inconclusive at the regional level. The interaction effects are insignificant both in the short and the long run. The patterns observed at the country level are therefore not confirmed. However, the results at least do not give proof of the contrary.

## Energy intensive industries, related and unrelated variety, and economic performance

In this section, the influence on regional employment growth of the share of industries that are exposed to a significant risk of carbon leakage according to the European Commission (Directive 2003/87/EC, see Box A.) is investigated. When the analysis in Table 5.3 of chapter 5 is repeated with the employment share of these industries replacing the general employment share of manufacturing (see Table A.11), this variable has no significant effect on regional employment growth over the time period considered. The conclusions regarding the main variables of interest remain unchanged (cf. section 5.3.2), although it is noticeable that the effect of unrelated variety increases slightly. Therefore, having a high share of industries potentially exposed to carbon leakage does not seem to be a threat to regional employment growth according to these estimates. However, this applies to the definition considering trade- and energy-intensive industries combined.

**Table A.11 Employment growth, related and unrelated variety in production and carbon leakage, Baseline and country regimes, Region level regressions, dependent variable = annual employment growth**

| | NUTS2 regions | | | | |
|---|---|---|---|---|---|
| | Panel Fixed Effects Estimator | | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| **Dependent Variable:** | **Coeff.** | **Coeff.** | **Coeff.** | **Country regimes** | |
| **Annual employment growth** | **(p-value)** | **(p-value)** | **(p-value)** | **Non-crisis** | **Crisis** |
| Lagged ln (related variety) | 0.004 | 0.010 | 0.013 | 0.047 ** | 0.075 |
| | (0.886) | (0.742) | (0.648) | (0.027) | (0.222) |
| Lagged ln (unrelated variety) | 0.169 *** | 0.179 *** | 0.160 *** | -0.023 | 0.357 *** |
| | (0.001) | (0.001) | (0.004) | (0.569) | (0.014) |
| Lagged product sophistication | | -0.019 | -0.024 | -0.008 | -0.057 |
| | | (0.285) | (0.161) | (0.592) | (0.500) |
| Lagged ln (specialisation) | | | -0.013 | -0.002 | -0.035 |
| | | | (0.204) | (0.840) | (0.376) |
| Lagged ln (population density) | | | 0.087 | 0.069 | 0.205 |
| | | | (0.645) | (0.548) | (0.704) |
| Lagged ln (wage rate) | | | 0.032 | 0.029 | -0.005 |
| | | | (0.159) | (0.112) | (0.962) |
| Lagged ln (investment per worker) | | | 0.008 | 0.023 | 0.021 |
| | | | (0.697) | (0.114) | (0.552) |
| Lagged (employment share carbon leakage industries) | | | 0.035 | 0.019 | 0.139 |
| | | | (0.488) | (0.670) | (0.225) |
| Time Dummies | YES | YES | YES | YES | YES |
| Region Dummies | YES | YES | YES | YES | YES |
| Number of Observations | 750 | 750 | 750 | 750 | 750 |
| Number of Regions | 250 | 250 | 250 | 250 | 250 |
| $R^2$ | 0.295 | 0.298 | 0.311 | 0.361 | 0.361 |

*Note: Robust p-values in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively*
*Source: WIFO calculations*

When focusing on energy-intensive industries only (see Table A.12), a negative effect on regional employment growth that is marginally significant (at the 10.4% level) does emerge in the crisis regions. Hence, for the countries most strongly affected by the crisis, all of which are peripheral countries, it seems particularly important to build their comparative advantage on advanced skills and innovation capabilities rather than on energy costs. Given the volatility of energy prices in recent years and the EU's general cost disadvantage vis-à-vis the United States for example, relying on industries requiring low energy costs appears to be a risky strategy.

**Table A.12 Employment growth, related and unrelated variety in production and energy-intensive industries, Baseline and country regimes, Region level regressions, dependent variable = annual employment growth**

| | NUTS2 regions | | | | |
|---|---|---|---|---|---|
| | Panel Fixed Effects Estimator | | | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| **Dependent Variable:** | **Coeff.** | **Coeff.** | **Coeff.** | **Country regimes** | |
| **Annual employment growth** | **(p-value)** | **(p-value)** | **(p-value)** | **Non-crisis** | **Crisis** |
| Lagged ln (related variety) | 0.004 | 0.010 | 0.010 | 0.046 ** | 0.044 |
| | (0.886) | (0.742) | (0.718) | (0.035) | (0.485) |
| Lagged ln (unrelated variety) | 0.169 *** | 0.179 *** | 0.164 *** | -0.028 | 0.355 *** |
| | (0.001) | (0.001) | (0.002) | (0.473) | (0.006) |
| Lagged product sophistication | | -0.019 | -0.022 | -0.007 | -0.047 |
| | | (0.285) | (0.196) | (0.617) | (0.546) |
| Lagged ln (specialisation) | | | -0.003 | -0.001 | -0.007 |
| | | | (0.273) | (0.667) | (0.499) |
| Lagged ln (population density) | | | 0.088 | 0.070 | 0.131 |
| | | | (0.633) | (0.549) | (0.806) |
| Lagged ln (wage rate) | | | 0.033 | 0.030 | -0.012 |
| | | | (0.153) | (0.108) | (0.903) |
| Lagged ln (investment per worker) | | | 0.009 | 0.019 | -0.013 |
| | | | (0.666) | (0.184) | (0.706) |
| Lagged (employment share energy-intensive industries) | | | -0.070 | 0.039 | -0.225 |
| | | | (0.390) | (0.506) | (0.104) |
| Time Dummies | YES | YES | YES | YES | YES |
| Region Dummies | YES | YES | YES | YES | YES |
| Number of Observations | 750 | 750 | 750 | 750 | 750 |
| Number of Regions | 250 | 250 | 250 | 250 | 250 |
| $R^2$ | 0.295 | 0.298 | 0.310 | 0.361 | 0.361 |

*Note: Robust p-values in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively*
*Source: WIFO calculations*

The analysis in Table 5.5, which investigates the effects of related and unrelated variety according to regional differences in terms of distance to the frontier and urban density, is also repeated using the employment shares of all industries defined as potentially affected by carbon leakage as well as of energy-intensive industries only. Neither variable has a significant association with employment growth in any of these regressions (results not presented here). The remaining estimates also do not change significantly.

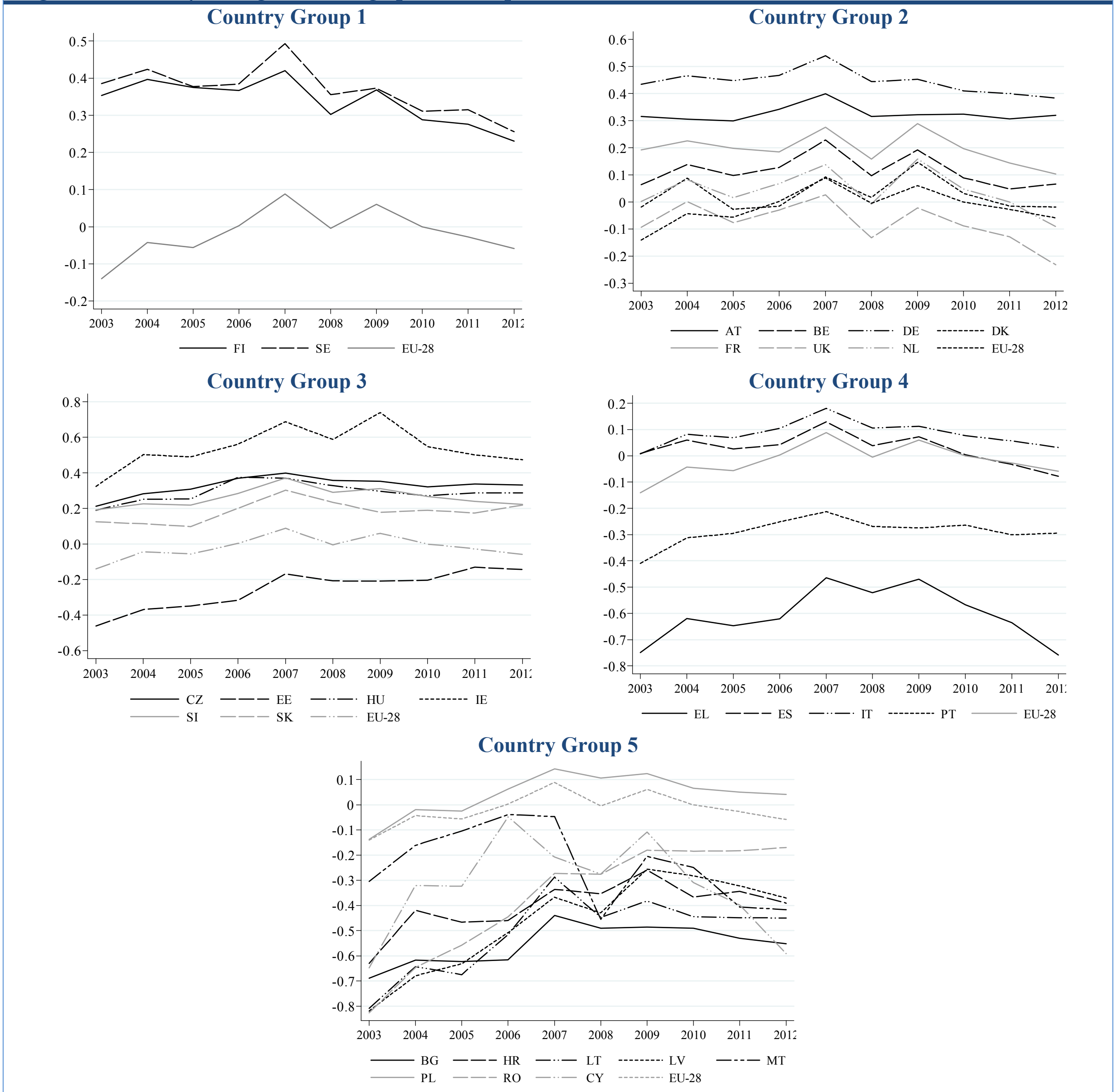
## Summary and conclusions

Summarising, the empirical evidence shows that the EU Member States are less specialised in energy intensive industries but show a comparably high degree of specialisation in industries potentially affected by carbon leakage (incl. trade intensive industries). The evidence also hints at a lower importance of related capabilities for specializing in energy intensive products. On the contrary, the more trade intensive a product is the more important it is to have related capabilities for maintaining or improving competitiveness. Countries are more often specialised in products produced by industries classified as potentially affected by carbon leakage if their productive structures are overall more closely related to these industries.

Specialising in a product is more difficult for more sophisticated products. The higher the sophistication of products the lower the number of countries exporting a product as entering these markets requires higher levels of capabilities. Although the evidence indicates that gaining world market shares in more sophisticated products is independent of whether the industry is energy intensive or not, it also shows that specialising in these products is more difficult for EU Member States. However, when looking at the importance of the share of energy intensive industries on employment growth weak, evidence is found that high shares of energy intensive industries are dangerous for countries with low levels of local capabilities. If these countries cannot base their comparative advantage on skills, they are likely to face high risks in times of economic crises and are probably heavily affected from volatile energy prices. The existence of local capabilities, i.e. specialising in high-end products, seems to temper these risks.

## A.3. APPENDIX TO CHAPTER 2

**Figure A.4 Yearly change of average product sophistication, EU-28 countries**




*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

### Issues of endogeneity in estimating world market shares using costs and prices of exports

The principal goal of the econometric models specified in this study is to examine the relationship between untraded interdependencies such as knowledge or coordination spillovers between related activities and the domestic competitiveness measured by world market shares domestic exporters obtain in a product class. Next to these factors a number of other factors are likely to affect export competitiveness, most importantly domestic costs of production that should be taken into account. However, as the following exposition will show this is not only difficult due to the lack of adequate data at the levels of aggregation the analysis is carried out, but also for strictly methodological reasons. The econometric analysis presented in Chapter 2 of the report is based on the considerations put forward in this appendix. The exposition draws on Reinstaller (2015).

World market shares $s_{c,p,t}$ of country *c* in year *t* in a product class *p* are a ratio of export values $v_{c,p,t}$ in that product class relative to total export values $V_{c,t}$ country c has obtained in year *t*. The export value itself is defined as

$$v_{c,p,t} = q_{c,p,t}p_{c,p,t},$$

and world market shares are given by

$$s_{c,p,t} = \frac{v_{c,p,t}}{V_{c,t}},$$

From economic theory prices are typically defined as

$$\bar{p}_{c,p,t} = (1 + \bar{\mu}_{c,p,t})\bar{h}_{c,p,t},$$

i.e. a mark-up $\bar{\mu}_{c,p,t}$ over average unit costs of production $\bar{h}_{c,p,t}$ with $\bar{h}_{c,p,t} = \bar{w}_{c,p,t}\bar{a}_{c,p,t} + \overline{pe}_{c,p,t}\bar{b}_{c,p,t} + (r_{c,p,t} + d_{c,p,t})\overline{pc}_{c,p,t}\bar{c}_{c,p,t}$. Parameters $\bar{w}_{c,p,t}$, $\overline{pe}_{c,p,t}$, and $\overline{pc}_{c,p,t}$ correspond to wages, energy prices and capital costs per unit respectively, and parameters $\bar{a}_{c,p,t}$, $\bar{b}_{c,p,t}$, and $\bar{c}_{c,p,t}$ correspond to the inputs of labour, energy and capital needed per unit of output. Finally, $r_{c,p,t}$ and $d_{c,p,t}$ reflect the cost of capital and the depreciation rate. In order to ensure consistency with the disaggregated trade data all these parameters are expressed as country specific means (overlining) over all exporters of a specific product class *p*.

Standard economic cost theory assumes that parameters $\bar{a}_{c,p,t}$, $\bar{b}_{c,p,t}$, and $\bar{c}_{c,p,t}$ are a function of output $q_{c,p,t}$. Under decreasing returns all three parameters would be increasing in $q_{c,p,t}$. However, also cost curves in which they are either constant or decreasing can be envisaged. Moreover, while energy and prices for capital inputs in most cases would be exogenous to a single market or producers operating on these markets, what matters for prices is the cost per unit of output and as input per unit of output changes with $q_{c,p,t}$, unit capital or energy costs cannot be used as controls in econometric estimations examining the relationship between market shares $s_{c,p,t}$ and prices $\bar{p}_{c,p,t}$ because they are endogenous. Only in case of constant costs endogeneity would not be an issue. To imply such cost curves for all types of products would be a very strong assumption. Problems are exacerbated for labour costs, as in the case of labour also wages, following standard theory, would be a function of output (as labour demand changes as a function of output). Hence, using unit cost measures in regressions with market shares as dependent variable is problematic as both dependent and independent variables are (generally) determined by physical output $q_{c,p,t}$.

A potential work around for this problem can be derived as follows. The world market share $s_{c,p,t}$ can be defined as

$$s_{c,p,t} = s_{c,p,t-1} + \Delta s_{c,p,t,}$$

and

$$\Delta s_{c,p,t} = s_{c,p,t-1}(g_{c,p,t} - \bar{g}_{p,t}) = s_{c,p,t-1}\Delta g_{c,p,t,}.$$

In first equation $\Delta s_{c,p,t}$ corresponds to a change in market shares between time *t* and *t-1*, and in the second equation $g_{c,p,t}$ is the growth rate of domestic exports for product *p* in the time interval between *t-1* and *t*. Parameter $\bar{g}_{p,t}$ is instead the average growth rate of exports of product *p* across all exporters in the same time interval. Hence, a country *c* will gain market shares if its exports given its initial market share grow faster than global exports of product *p*. Following Metcalfe (1998), the growth rate differential can now be defined as follows: The growth of physical output of domestic exporters will be determined by their reinvestment of profits into new capital goods:

$$g_{c,p,t} = \bar{f}_{c,p,t}(\bar{p}_{c,p,t} - \bar{h}_{c,p,t}).$$

In this equation $\bar{f}_{c,p,t}$ captures the average share of reinvested profits for capital adjustment. On the demand side the growth of demand for domestic products will be determined by

$$g_{Dc,p,t} = \bar{g}_{p,t} - \delta_{c,p,t}(\bar{p}_{p,t} - \bar{p}_{c,p,t}),$$

where $\delta_{p,t}$ is a parameter capturing market imperfection in terms of switching costs on the demand side. If these are high $\delta_{p,t}$ will be small and deviation of domestic prices from average world prices $\bar{p}_{p,t}$ in product group *p* will translate only into mild deviations from the global growth rate. If switching costs are low $\delta_{p,t}$ will be very high and slightest deviations of domestic producers from world market prices will be lead to sharp gains or losses in market shares. In equilibrium the two growth rates will be equal and firms will chose a price that balances investment plans with demand development. This price is obtained by equating the two equations and solving for price. Plugging this equilibrium price into the first equation for the growth of physical output of domestic exporters and subtracting $\bar{g}_{p,t}$, one obtains

$$\Delta g_{c,p,t} = \frac{\delta_{c,p,t}}{\bar{f}_{c,p,t} + \delta_{c,p,t}} \bar{g}_{p,t} + \frac{\bar{f}_{c,p,t}\delta_{c,p,t}}{\bar{f}_{c,p,t} + \delta_{c,p,t}} \bar{p}_{p,t} + \left[\bar{f}_{c,p,t} + \frac{\bar{f}^2_{c,p,t}}{\bar{f}_{c,p,t} + \delta_{c,p,t}}\right] \bar{h}_{c,p,t}.$$

Now the growth rate differential that determines the change in market shares $s_{c,p,t}$ for any obtained market share $s_{c,p,t-1}$ is expressed as a function of global demand development, world average market prices and domestic average unit costs as well as domestic industry specific accumulation rules and switching costs that govern the intensity of competition.

Given this analytical result in specifying the econometric models examining the relationship between untraded interdependencies and world market shares presented in Chapter 2 we have added

- a control for world market development $\bar{g}_{p,t}$ using the log of the world market and the time average of the log of the world market share (logMS)
- domestic import prices for $\bar{p}_{p,t}$ (cFPI)
- a control for the intensity of competition $\delta_{p,t}$ proxied by the Grubel-Lloyd index (GLI),
- 2-digit sector dummies to control for other unobserved sector specific characteristics such as accumulation rules or minimum efficient scales,
- and the Herfindahl index at the 6-digit trade class level (HERF) as well as the product relatedness (ProdRel) indicator to capture unit costs.

The choice of the price index and the proxies for unit cost need some further explanation. Concerning the price index the model would suggest using an average price index of *world market prices*. However, in the face of vertical differentiated markets such a price measure would be too unspecific and potentially induce unwanted noise. One has therefore to think about a proxy for world market prices relevant to domestic exporters. As influential contributions to trade theory and empirics have shown that intra-industrial trade happens mostly between countries with similar levels of economic development we have adopted import prices as a proxy for relevant (exogenous) price signals to domestic exporters. The reasoning is that for domestic exporters competitors in the same product class that are active in very different (e.g. lower quality and lower cost) market segments and for which there is no demand by domestic customers are not relevant. Rather they care mostly about competitors that are also imported by domestic customers and hence compete with their products on the domestic market.

The reasoning for the choice of the proxies for unit costs is as follows. Unit costs $\bar{h}_{c,p,t}$ can be expressed as a function of different processes that go along with locally increasing returns: $\bar{h}_{c,p,t} = f(v_{c,p,t}, L_{c,p,t}, E_{c,p,t})$. Variable $v_{c,p,t}$ stands for current output and reflects returns to scale on unit cost. They will fall in $v_{c,p,t}$ if the production of product *p* is scale elastic. Function $L_{c,p,t} = \Phi(\sum v_{c,p,t})$ captures the effects of product specific learning on unit costs through the past experience (e.g. learning by doing). Finally, $E_{c,p,t} = \Theta(\omega_{pq,c})$ is the effect of untraded interdependencies $\omega_{pq}$ between products *p* and *q* in country *c*. The latter is of predominant interest for the present analysis and is captured in the analysis by the product relatedness indicator ProdRel. The former two suffer from endogeneity issues as explained before and are to some extent also not observable. However, following economic theory one can argue that a higher level of sunk costs such as cumulated advertising outlays, R&D spending and accumulated tacit experience are characteristic of more concentrated industries. Hence, we use the Herfindahl index as a proxy for these types of cost factors.

## A.4. APPENDIX TO CHAPTER 3

**Table A.13 Robustness checks baseline regressions in chapter 3, EU-28 countries, dependent variable = standardised revealed comparative advantage (srca)**

| | OLS | FE | RE | FRM |
|---|---|---|---|---|
| Lagged dependent variable, (L.srca) | 0.827 *** | 0.345 *** | 0.827 *** | 2.210 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Dep.Variable time t=0, (srcat=0) | | | | 0.446 *** |
| | | | | (0.000) |
| Neighbourhood density, dens | 0.376 *** | 0.306 *** | 0.376 *** | 6.445 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Neighbourhood density (LR), dens_mean | | | | -3.683 *** |
| | | | | (0.000) |
| Product sophistication, soph | 0.002 *** | 0.001 * | 0.002 *** | 0.020 *** |
| | (0.000) | (0.087) | (0.000) | (0.000) |
| Product sophistication (LR), soph_mean | | | | -0.015 *** |
| | | | | (0.000) |
| Constant | -0.121 *** | 0.095 *** | -0.014 *** | -2.227 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 1,256,391 | 1,256,391 | 1,256,391 | 1,255,743 |
| R-squared | 0.794 | 0.143 | 0.766 | 0.818 |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |

*Note: Coefficients represent estimated coefficients. p-Values in parentheses*
*Source: WIFO calculations*

**Table A.14 Robustness checks baseline regressions in chapter 3, EU-28 countries, dependent variable = world market shares (wms)**

| | OLS | FE | RE | FRM |
|---|---|---|---|---|
| Lagged dependent variable, (L.wms) | 0.887 *** | 0.409 *** | 0.887 *** | 3.235 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Dep.Variable time t=0, (wmst=0) | | | | 0.696 *** |
| | | | | (0.000) |
| Neighbourhood density, dens | 0.013 *** | 0.007 *** | 0.013 *** | 3.948 *** |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| Neighbourhood density (LR), dens_mean | | | | 0.656 *** |
| | | | | (0.000) |
| Product sophistication, soph | 0.000 *** | 0.000 ** | 0.000 *** | -0.007 ** |
| | (0.000) | (0.021) | (0.000) | (0.016) |
| Product sophistication (LR), soph_mean | | | | -0.005 * |
| | | | | (0.084) |
| Constant | -0.003 *** | 0.006 *** | -0.002 *** | -3.675 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 1256391 | 1,256,391 | 1,256,391 | 1,255,743 |
| R-squared | 0.862 | 0.163 | 0.86056 | 0.796 |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |

*Note: Coefficients represent estimated coefficients. p-Values in parentheses*
*Source: WIFO calculations*

**Table A.15 Robustness checks baseline regressions in chapter 3, pooled world sample, dependent variable = standardised revealed comparative advantage (srca)**

| | OLS | FE | RE | FRM |
|---|---|---|---|---|
| Lagged dependent variable, (L.srca) | 0.831 *** | 0.320 *** | 0.831 *** | 2.310 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Dep.Variable time t=0, (srcat=0) | | | | 0.576 *** |
| | | | | (0.000) |
| Neighbourhood density, dens | 0.339 *** | 0.273 *** | 0.339 *** | 6.265 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Neighbourhood density (LR), dens_mean | | | | -4.042 *** |
| | | | | (0.000) |
| Product sophistication, soph | 0.002 *** | 0.001 *** | 0.002 *** | 0.004 *** |
| | (0.000) | (0.000) | (0.000) | (0.008) |
| Product sophistication (LR), soph_mean | | | | -0.003 ** |
| | | | | (0.047) |
| Constant | -0.099 *** | 0.091 *** | -0.015 *** | -2.194 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 3,210,777 | 3,210,777 | 3,210,777 | 3,209,121 |
| R-squared | 0.797 | 0.120 | 0.769 | 0.815 |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |

*Note: Coefficients represent estimated coefficients. p-Values in parentheses*
*Source: WIFO calculations*

**Table A.16 Robustness checks baseline regressions in chapter 3, pooled world sample, dependent variable = world market shares (wms)**

| | OLS | FE | RE | FRM |
|---|---|---|---|---|
| Lagged dependent variable, (L.wms) | 0.902 *** | 0.416 *** | 0.902 *** | 2.997 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Dep.Variable time t=0, (wmst=0) | | | | 0.76 *** |
| | | | | (0.000) |
| Neighbourhood density, dens | 0.013 *** | 0.008 *** | 0.013 *** | 3.844 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Neighbourhood density (LR), dens_mean | | | | 0.587 *** |
| | | | | (0.000) |
| Product sophistication, soph | 0.000 *** | 0.000 | 0.000 *** | -0.008 *** |
| | (0.000) | (0.560) | (0.000) | (0.001) |
| Product sophistication (LR), soph_mean | | | | 0.012 *** |
| | | | | (0.000) |
| Constant | -0.000 | 0.006 *** | -0.001 *** | -3.655 *** |
| | (0.360) | (0.000) | (0.000) | (0.000) |
| Observations | 3,210,777 | 3,210,777 | 3,210,777 | 3,209,121 |
| R-squared | 0.852 | 0.156 | 0.849519 | 0.789 |
| Time Dummies | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES |

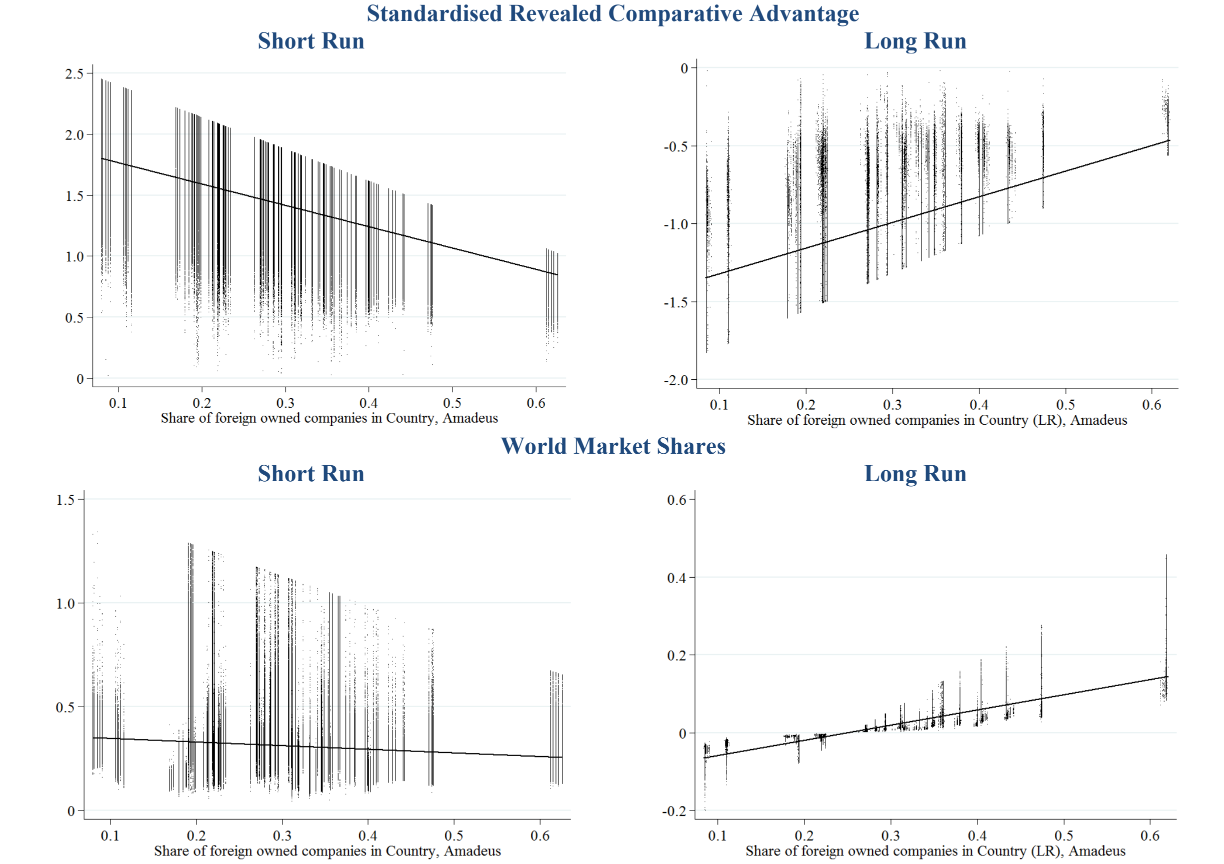
*Note: Coefficients represent estimated coefficients. p-Values in parentheses*
*Source: WIFO calculations*

**Table A.17 Specialisation, product space and knowledge capabilities, product level regressions, sample of EU-28 vs. world countries, dependent variable = Standardised revealed comparative advantage (SRCA)**

| | EU-28 countries | | | | Pooled sample (incl. non-EU countries) | | | |
|---|---|---|---|---|---|---|---|---|
| | | QML Flogit Estimator | | | | QML Flogit Estimator | | |
| **Model** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| **Dependent Variable:** | **APE** | **Sign** | **Sign** | **Sign** | **APE** | **Sign** | **Sign** | **Sign** |
| **Standardised revealed comparative advantage, srca** | **(p-value)** | | | | **(p-value)** | | | |
| Lagged standardised revealed comparative advantage L.srca | 0.504 *** | +++ | +++ | +++ | 0.431 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Standardised revealed comparative advantage time t=0, $srca_{t=0}$ | 0.103 *** | +++ | +++ | +++ | 0.108 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density, dens | 1.494 *** | +++ | +++ | +++ | 1.192 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Neighbourhood density (LR), dens_mean | -0.880 *** | --- | --- | --- | -0.781 *** | --- | --- | --- |
| | (0.000) | | | | (0.000) | | | |
| Product sophistication, soph | 0.005 *** | +++ | +++ | + | 0.001 ** | +++ | +++ | + |
| | (0.000) | | | | (0.011) | | | |
| Product sophistication (LR), soph_mean | -0.003 *** | --- | --- | --- | -0.000 | --- | 0 | --- |
| | (0.000) | | | | (0.213) | | | |
| Average years of schooling, sch | 0.008 *** | +++ | +++ | +++ | 0.009 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Average years of schooling (LR), sch_mean | 0.626 *** | +++ | +++ | +++ | 0.379 *** | +++ | +++ | +++ |
| | (0.000) | | | | (0.000) | | | |
| Interaction Neighb.density x Av. Years of schooling | | 0 | 0 | | | --- | --- | |
| Interaction Neighb.density x Av. Years of schooling (LR) | | +++ | +++ | | | +++ | +++ | |
| Interaction Prod. Soph. x Av. Years of schooling | | --- | | --- | | --- | | --- |
| Interaction Prod. Soph. x Av. Years of schooling (LR) | | +++ | | +++ | | +++ | | +++ |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 1,255,743 | 1,255,743 | 1,255,743 | 1,255,743 | 3,209,121 | 3,209,121 | 3,209,121 | 3,209,121 |
| Pseudo $R^2$ | 0.819 | 0.819 | 0.819 | 0.819 | 0.816 | 0.816 | 0.816 | 0.816 |
| Deviance | 140889 | 140717 | 140862 | 140724 | 365527 | 365231 | 365327 | 365476 |
| Log Pseudolikelihood | -373709 | -373623 | -373695 | -373626 | -805876 | -805728 | -805776 | -805850 |
| Wald-Test (Time Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald-Test (Country Dummies) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: APE represent average partial effects. p-Values in parentheses. "Sign" represents the direction of the effect: +++, ++, + ... positively significant on the 1%, 5% and 10%-level respectively: ---, --, - ... negatively significant on the 1%, 5% and 10%-level respectively. 0 ... not significantly deviating from zero*
*Source: WIFO calculations*

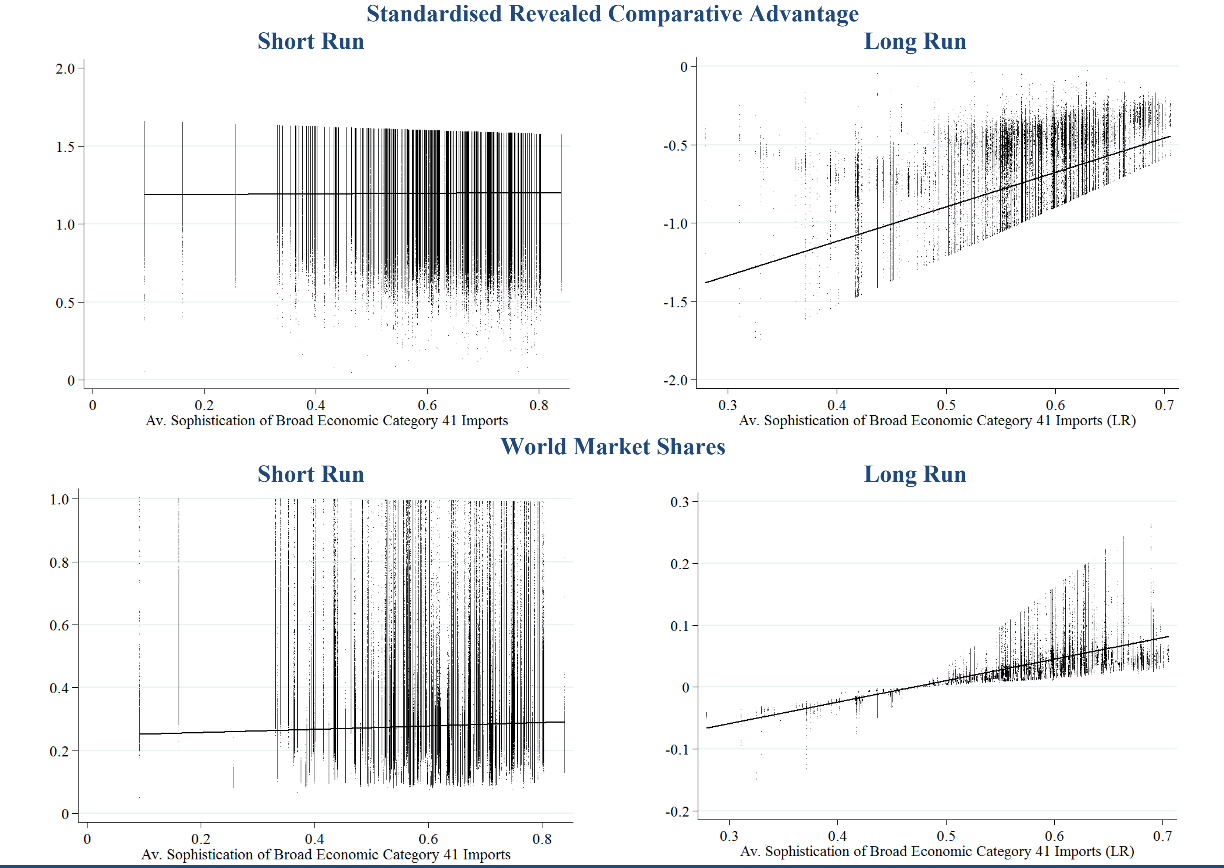
**Figure A.5 The effect of product neighbourhood density on comparative advantage and world market shares depending on the share of foreign owned firms in the country's manufacturing sector, sample of EU-28 countries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*

*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010), Bureau van Dijk (Amadeus)*

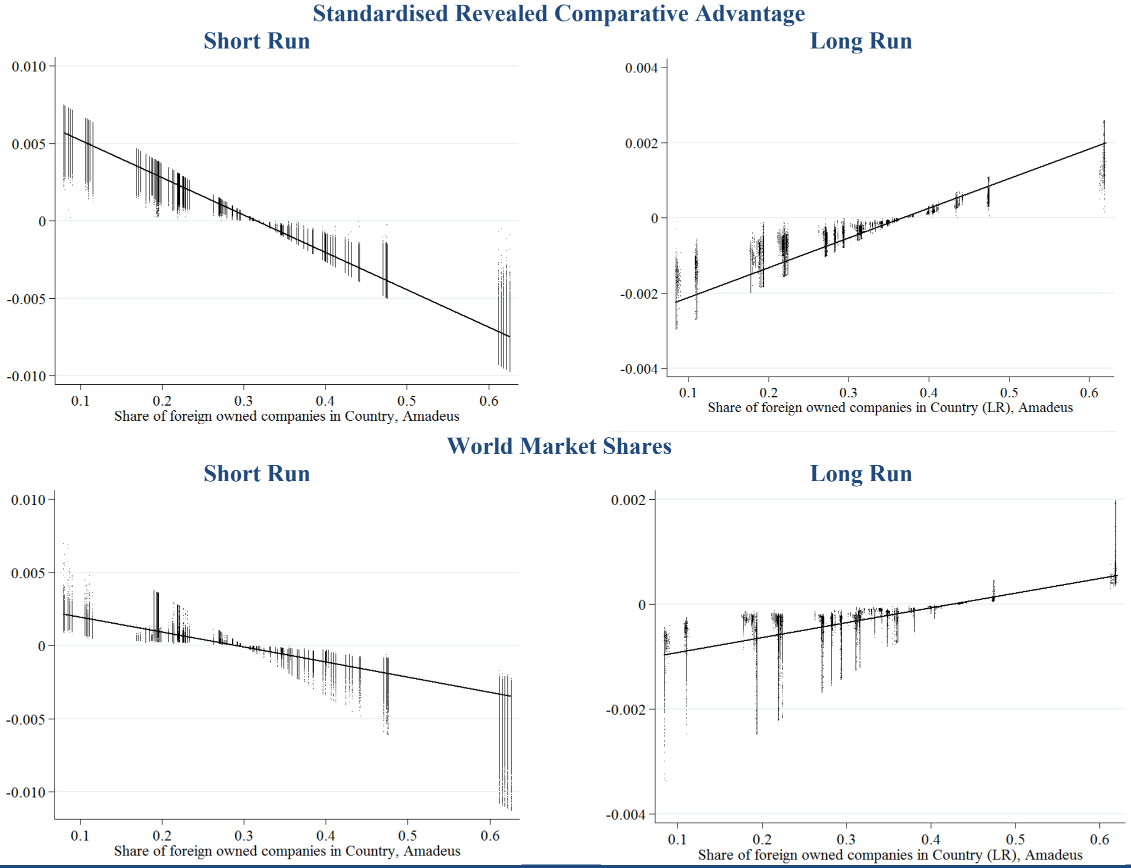
**Figure A.6 The effect of product neighbourhood density on comparative advantage and world market shares depending on the sophistication of capital goods imports, sample of EU-28 countries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*

*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010), Bureau van Dijk (Amadeus)*

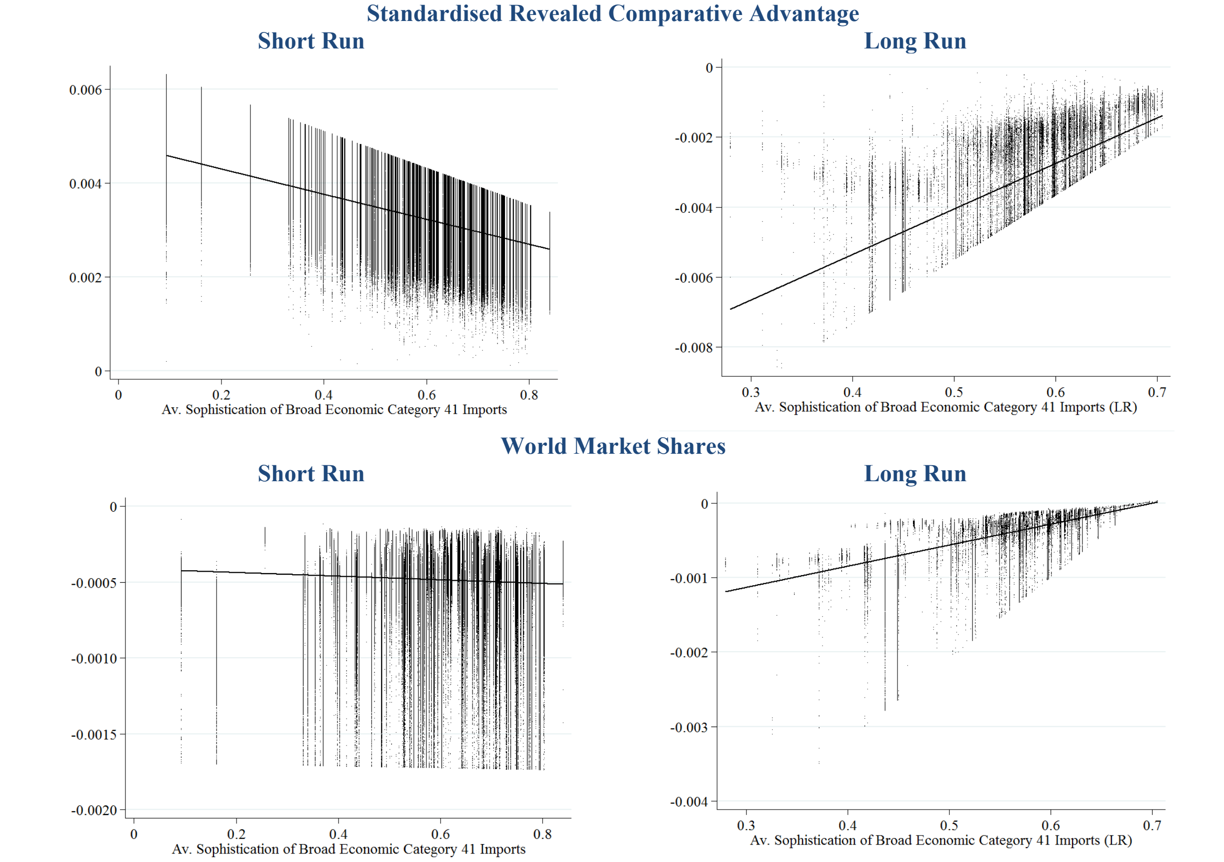
**Figure A.7 The effect of product sophistication on comparative advantage and world market shares depending on the share of foreign owned firms in the country's manufacturing sector, sample of EU-28 countries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*

*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010), Bureau van Dijk (Amadeus)*

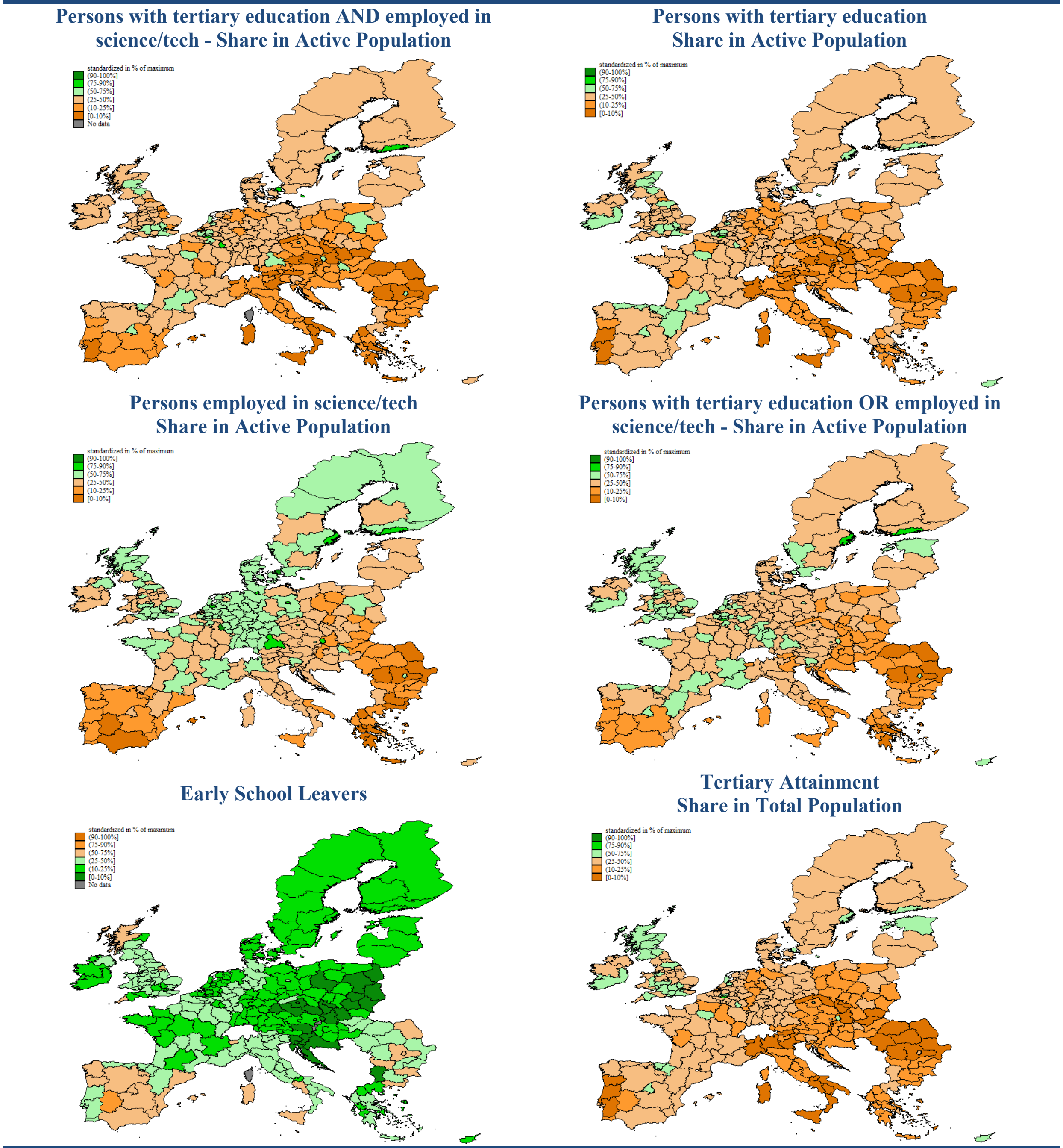
**Figure A.8 The effect of product sophistication on comparative advantage and world market shares depending on the sophistication of capital goods imports, sample of EU-28 countries**




*Note: Figure shows magnitude of the overall partial effects of one variable on the dependent variable taking into account the interaction effect for different levels of the other interacted independent variable. Vertical variation of the effects occur due to differences in the values of the covariates ($V_i$) per observation*
*Source: WIFO calculations. BACI dataset (Gaulier and Zignago 2010)*

## A.5. Appendix to Chapter 4

**Figure A.9 Regional indicators on education skills (2012) – a comparison**




*Note: Values are standardised: 0 ... minimum, 1 ... maximum in sample. Please note reverse scale for the indicator Early School Leavers!*
*Source: Eurostat*

## A.6. NACE Rev 2 Industry Classification

**Table A.18 Description of NACE Rev. 2 2-digit industries in the manufacturing sector**

| | |
|---|---|
| 10 | Manufacture of food products |
| 11 | Manufacture of beverages |
| 12 | Manufacture of tobacco products |
| 13 | Manufacture of textiles |
| 14 | Manufacture of wearing apparel |
| 15 | Manufacture of leather and related products |
| 16 | Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials |
| 17 | Manufacture of paper and paper products |
| 18 | Printing and reproduction of recorded media |
| 19 | Manufacture of coke and refined petroleum products |
| 20 | Manufacture of chemicals and chemical products |
| 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| 22 | Manufacture of rubber and plastic products |
| 23 | Manufacture of other non-metallic mineral products |
| 24 | Manufacture of basic metals |
| 25 | Manufacture of fabricated metal products, except machinery and equipment |
| 26 | Manufacture of computer, electronic and optical products |
| 27 | Manufacture of electrical equipment |
| 28 | Manufacture of machinery and equipment n.e.c. |
| 29 | Manufacture of motor vehicles, trailers and semi-trailers |
| 30 | Manufacture of other transport equipment |
| 31 | Manufacture of furniture |
| 32 | Other manufacturing |

*Source: Eurostat*

# A.7. CARBON LEAKAGE AFFECTED INDUSTRIES

**Table A.19 List of carbon leakage affected industries[70]**

**1. BASED ON THE CRITERIA SET OUT IN ARTICLE 10a(15) AND (16) OF DIRECTIVE 2003/87/EC**

**1.1. At the NACE-4 level**

| NACE Code | Description | Criteria met |
|---|---|---|
| 893 | Extraction of salt | A |
| 1062 | Manufacture of starches and starch products | A |
| 1081 | Manufacture of sugar | A |
| 1104 | Manufacture of other non-distilled fermented beverages | A |
| 1712 | Manufacture of paper and paperboard | A |
| 1920 | Manufacture of refined petroleum products | A |
| 2311 | Manufacture of flat glass | A |
| 2313 | Manufacture of hollow glass | A |
| 2410 | Manufacture of basic iron and steel and of ferro-alloys | A |
| 2443 | Lead, zinc and tin production | A |
| 2015 | Manufacture of fertilisers and nitrogen compounds | A, B |
| 899 | Other mining and quarrying n.e.c. | A, C |
| 1711 | Manufacture of pulp | A, C |
| 1910 | Manufacture of coke oven products | A, C |
| 2013 | Manufacture of other inorganic basic chemicals | A, C |
| 2014 | Manufacture of other organic basic chemicals | A, C |
| 2331 | Manufacture of ceramic tiles and flags | A, C |
| 2442 | Aluminium production | A, C |
| 2446 | Processing of nuclear fuel | A, C |
| 2314 | Manufacture of glass fibres | A, C |
| 2351 | Manufacture of cement | B |
| 2352 | Manufacture of lime and plaster | B |
| 510 | Mining of hard coal | C |
| 610 | Extraction of crude petroleum | C |
| 620 | Extraction of natural gas | C |
| 710 | Mining of iron ores | C |
| 729 | Mining of other non-ferrous metal ores | C |
| 891 | Mining of chemical and fertiliser minerals | C |
| 1020 | Processing and preserving of fish, crustaceans and molluscs | C |
| 1041 | Manufacture of oils and fats | C |
| 1086 | Manufacture of homogenised food preparations and dietetic food | C |
| 1101 | Distilling, rectifying and blending of spirits | C |
| 1102 | Manufacture of wine from grape | C |
| 1310 | Preparation and spinning of textile fibres | C |
| 1320 | Weaving of textiles | C |
| 1391 | Manufacture of knitted and crocheted fabrics | C |
| 1392 | Manufacture of made-up textile articles, except apparel | C |
| 1393 | Manufacture of carpets and rugs | C |
| 1394 | Manufacture of cordage, rope, twine and netting | C |
| 1395 | Manufacture of non-wovens and articles made from non-wovens, except apparel | C |
| 1396 | Manufacture of other technical and industrial textiles | C |
| 1399 | Manufacture of other textiles n.e.c. | C |
| 1411 | Manufacture of leather clothes | C |
| 1412 | Manufacture of workwear | C |
| 1413 | Manufacture of other outerwear | C |
| 1414 | Manufacture of underwear | C |
| 1419 | Manufacture of other wearing apparel and accessories | C |
| 1420 | Manufacture of articles of fur | C |
| 1431 | Manufacture of knitted and crocheted hosiery | C |
| 1439 | Manufacture of other knitted and crocheted apparel | C |
| 1511 | Tanning and dressing of leather; dressing and dyeing of fur | C |
| 1512 | Manufacture of luggage, handbags and the like, saddlery and harness | C |
| 1520 | Manufacture of footwear | C |
| 1622 | Manufacture of assembled parquet floors | C |

[70] http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32014D0746&from=EN

| | | |
|---|---|---|
| 1629 | Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials | C |
| 1724 | Manufacture of wallpaper | C |
| 2012 | Manufacture of dyes and pigments | C |
| 2016 | Manufacture of plastics in primary forms | C |
| 2017 | Manufacture of synthetic rubber in primary forms | C |
| 2020 | Manufacture of pesticides and other agrochemical products | C |
| 2042 | Manufacture of perfumes and toilet preparations | C |
| 2053 | Manufacture of essential oils | C |
| 2059 | Manufacture of other chemical products n.e.c. | C |
| 2060 | Manufacture of man-made fibres | C |
| 2110 | Manufacture of basic pharmaceutical products | C |
| 2120 | Manufacture of pharmaceutical preparations | C |
| 2211 | Manufacture of rubber tyres and tubes; retreading and rebuilding of rubber tyres | C |
| 2219 | Manufacture of other rubber products | C |
| 2319 | Manufacture and processing of other glass, including technical glassware | C |
| 2320 | Manufacture of refractory products | C |
| 2341 | Manufacture of ceramic household and ornamental articles | C |
| 2342 | Manufacture of ceramic sanitary fixtures | C |
| 2343 | Manufacture of ceramic insulators and insulating fittings | C |
| 2344 | Manufacture of other technical ceramic products | C |
| 2349 | Manufacture of other ceramic products | C |
| 2370 | Cutting, shaping and finishing of stone | C |
| 2391 | Production of abrasive products | C |
| 2420 | Manufacture of tubes, pipes, hollow profiles and related fittings, of steel | C |
| 2431 | Cold drawing of bars | C |
| 2441 | Precious metals production | C |
| 2444 | Copper production | C |
| 2445 | Other non-ferrous metal production | C |
| 2540 | Manufacture of weapons and ammunition | C |
| 2571 | Manufacture of cutlery | C |
| 2572 | Manufacture of locks and hinges | C |
| 2573 | Manufacture of tools | C |
| 2594 | Manufacture of fasteners and screw machine products | C |
| 2599 | Manufacture of other fabricated metal products n.e.c. | C |
| 2611 | Manufacture of electronic components | C |
| 2612 | Manufacture of loaded electronic boards | C |
| 2620 | Manufacture of computers and peripheral equipment | C |
| 2630 | Manufacture of communication equipment | C |
| 2640 | Manufacture of consumer electronics | C |
| 2651 | Manufacture of instruments and appliances for measuring, testing and navigation | C |
| 2652 | Manufacture of watches and clocks | C |
| 2660 | Manufacture of irradiation, electromedical and electrotherapeutic equipment | C |
| 2670 | Manufacture of optical instruments and photographic equipment | C |
| 2680 | Manufacture of magnetic and optical media | C |
| 2711 | Manufacture of electric motors, generators and transformers | C |
| 2712 | Manufacture of electricity distribution and control apparatus | C |
| 2720 | Manufacture of batteries and accumulators | C |
| 2731 | Manufacture of fibre optic cables | C |
| 2732 | Manufacture of other electronic and electric wires and cables | C |
| 2733 | Manufacture of wiring devices | C |
| 2740 | Manufacture of electric lighting equipment | C |
| 2751 | Manufacture of electric domestic appliances | C |
| 2752 | Manufacture of non-electric domestic appliances | C |
| 2790 | Manufacture of other electrical equipment | C |
| 2811 | Manufacture of engines and turbines, except aircraft, vehicle and cycle engines | C |
| 2812 | Manufacture of fluid power equipment | C |
| 2813 | Manufacture of other pumps and compressors | C |
| 2814 | Manufacture of other taps and valves | C |
| 2815 | Manufacture of bearings, gears, gearing and driving elements | C |
| 2821 | Manufacture of ovens, furnaces and furnace burners | C |
| 2822 | Manufacture of lifting and handling equipment | C |
| 2823 | Manufacture of office machinery and equipment (except computers and peripheral equipment) | C |
| 2824 | Manufacture of power-driven hand tools | C |

| | | |
|---|---|---|
| 2825 | Manufacture of non-domestic cooling and ventilation equipment | C |
| 2829 | Manufacture of other general-purpose machinery n.e.c. | C |
| 2830 | Manufacture of agricultural and forestry machinery | C |
| 2841 | Manufacture of metal forming machinery | C |
| 2849 | Manufacture of other machine tools | C |
| 2891 | Manufacture of machinery for metallurgy | C |
| 2892 | Manufacture of machinery for mining, quarrying and construction | C |
| 2893 | Manufacture of machinery for food, beverage and tobacco processing | C |
| 2894 | Manufacture of machinery for textile, apparel and leather production | C |
| 2895 | Manufacture of machinery for paper and paperboard production | C |
| 2896 | Manufacture of plastic and rubber machinery | C |
| 2899 | Manufacture of other special-purpose machinery n.e.c. | C |
| 2910 | Manufacture of motor vehicles | C |
| 2931 | Manufacture of electrical and electronic equipment for motor vehicles | C |
| 3011 | Building of ships and floating structures | C |
| 3012 | Building of pleasure and sporting boats | C |
| 3030 | Manufacture of air and spacecraft and related machinery | C |
| 3091 | Manufacture of motorcycles | C |
| 3092 | Manufacture of bicycles and invalid carriages | C |
| 3099 | Manufacture of other transport equipment n.e.c. | C |
| 3109 | Manufacture of other furniture | C |
| 3211 | Striking of coins | C |
| 3212 | Manufacture of jewellery and related articles | C |
| 3213 | Manufacture of imitation jewellery and related articles | C |
| 3220 | Manufacture of musical instruments | C |
| 3230 | Manufacture of sports goods | C |
| 3240 | Manufacture of games and toys | C |
| 3250 | Manufacture of medical and dental instruments and supplies | C |
| 3291 | Manufacture of brooms and brushes | C |
| 3299 | Other manufacturing n.e.c. | C |

**2. BASED ON THE CRITERIA SET OUT IN ARTICLE 10a(17) OF DIRECTIVE 2003/87/EC**

| NACE Code | Description |
|---|---|
| 1106 | Manufacture of malt |
| 1330 | Finishing of textiles |
| 2332 | Manufacture of bricks, tiles and construction products, in baked clay |
| 2362 | Manufacture of plaster products for construction purposes |
| 2451 | Casting of iron |
| 2453 | Casting of light metals |

*Source: http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32014D0746&from=EN*

## Table A.20 Variables used in the report

| Variables | Sources | Coverage | Description | Further information | Used in Chapters |
|---|---|---|---|---|---|
| Specialisation and Competitiveness | | | | | |
| Country-Level | | | | | |
| Revealed Comparative Advantage (RCA) | CEPII (BACI) | World Countries, HS6 product classes | based on world exports | Box 2.1 | 2,3 |
| Standardised Revealed Comparative Advantage (SRCA) | CEPII (BACI) | World Countries, HS6 product classes | based on world exports | Box 2.1 | 2,3 |
| World Market Shares (WMS) | CEPII (BACI) | World Countries, HS6 product classes | based on world exports | Box 2.1 | 2,3 |
| NUTS2 regional level | | | | | |
| Revealed Comparative Advantage (RCA) | BvD (AMADEUS) | NUTS2, NACE 4-digit industries | based on employment shares within EU | Box 2.1, Section 4.1.1 | 4 |
| Standardised Revealed Comparative Advantage (SRCA) | BvD (AMADEUS) | NUTS2, NACE 4-digit industries | based on employment shares within EU | Box 2.1, Section 4.1.1 | 4 |
| Product Space | | | | | |
| Country-Level | | | | | |
| Product Neighbourhood Density (DENS) | CEPII (BACI) | World Countries, HS6 product classes | Relatedness of product class to country's industry structure | Box 2.2 | 2,3 |
| Product Sophistication (SOPH) | CEPII (BACI) | World Countries, HS6 product classes | Sophistication of product class | Table 2.1, Box 2.3 | 2,3 |
| NUTS2 regional level | | | | | |
| Product Neighbourhood Density (DENS) | CEPII (BACI), BvD (AMADEUS) | NUTS2, NACE 4-digit industries | Relatedness of product class to region's industry structure | Section 4.1.2 | 4 |
| Product Sophistication (SOPH) | CEPII (BACI), BvD (AMADEUS) | NUTS2, NACE 4-digit industries | Sophistication of product class | Section 4.1.2 | 4,5 |
| Related Variety - Production (RV) | BvD (AMADEUS) | NUTS2, NACE 4-digit industries | Distribution of economic activities within NACE 2-digit industries | Table 5.1, Box 5.1 | 5 |
| Unrelated Variety - Production (UV) | BvD (AMADEUS) | NUTS2, NACE 4-digit industries | Distribution of economic activities across NACE 2-digit industries | Table 5.1, Box 5.1 | 5 |
| Market Structure, Competition and Costs | | | | | |
| Herfindahl Index (HERF) | CEPII (BACI) | World Countries, HS6 product classes | Market Concentration | Section 2.4.2 | 2 |
| Grubel-Lloyd Index (GLI) | CEPII (BACI) | World Countries, HS6 product classes | Inter-Industry Trade | Section 2.4.2 | 2 |
| Chained Fisher Price Index of Imports (cFPI) | CEPII (BACI) | World Countries, HS6 product classes | Relative Price Levels | Section 2.4.2 | 2 |
| Log Market Size World (MS) | CEPII (BACI) | World Countries, HS6 product classes | World Market Size | Section 2.4.2 | 2 |
| Strategic Market Penetration (SMP) | CEPII (BACI) | World Countries, HS6 product classes | Penetration of larger and faster growing markets | Section 2.4.2 | 2 |
| Education and Skills | | | | | |
| Cognitive Skills | Hanushek & Wössmann | World Countries | Cognitive skills, all math and science (test score) | Section 3.1 | 3 |
| Share of top-performing students | Hanushek & Wössmann | World Countries | Share of top-performing students | Section 3.1 | 3 |
| Average Years of Schooling | Barro & Lee | World Countries | population aged 25 or older, interpolated | Section 3.1 | 3 |
| Primary Attainment | Barro & Lee | World Countries | Share of population (aged 25 or older), interpolated | Section 3.1 | 3 |
| Secondary Attainment | Barro & Lee | World Countries | Share of population (aged 25 or older), interpolated | Section 3.1 | 3 |
| Tertiary Attainment | Barro & Lee | World Countries | Share of population (aged 25 or older), interpolated | Section 3.1 | 3 |
| Tertiary Attainment | Eurostat | EU-28 countries, NUTS2 | Share of total population, interpolated | Sections 3.1 and 4.1.3 | 3,4 |
| Early School Leavers | Eurostat | EU-28 countries, NUTS2 | Share of total population, interpolated | Sections 3.1 and 4.1.3 | 3,4 |
| Persons with tertiary education OR employed in science/tech | Eurostat | EU-28 countries, NUTS2 | Share of active population | Sections 3.1 and 4.1.3 | 3,4 |
| Persons with tertiary education AND employed in science/tech | Eurostat | EU-28 countries, NUTS2 | Share of active population | Sections 3.1 and 4.1.3 | 3,4 |
| Persons with tertiary education | Eurostat | EU-28 countries, NUTS2 | Share of active population | Sections 3.1 and 4.1.3 | 3,4 |
| Persons employed in science/tech | Eurostat | EU-28 countries, NUTS2 | Share of active population | Sections 3.1 and 4.1.3 | 3,4 |
| Persons with tertiary education OR employed in science/tech | Eurostat | EU-28 countries, NUTS2 | Share of total employment | Sections 3.1 and 4.1.3 | 3,4 |
| Persons with tertiary education AND employed in science/tech | Eurostat | EU-28 countries, NUTS2 | Share of total employment | Sections 3.1 and 4.1.3 | 3,4 |
| Persons with tertiary education | Eurostat | EU-28 countries, NUTS2 | Share of total employment | Sections 3.1 and 4.1.3 | 3,4 |
| Persons employed in science/tech | Eurostat | EU-28 countries, NUTS2 | Share of total employment | Sections 3.1 and 4.1.3 | 3,4 |
| Knowledge Generation | | | | | |
| Patent neighbourhood density | OECD REGPAT | EU-28 countries, NUTS2 | Relatedness of product class to country's/region's patenting activities | Section 3.1 and 4.1.3 | 3,4 |
| Related Variety - Knowledge | OECD REGPAT | NUTS2, IPC 7-digit technology classes | Distribution of patenting activities within 3-digit IPC technology classes | Table 5.1, Box 5.2 | 5 |
| Unrelated Variety - Knowledge | OECD REGPAT | NUTS2, IPC 7-digit technology classes | Distribution of patenting activities across 3-digit IPC technology classes | Table 5.1, Box 5.2 | 5 |
| Knowledge Inflows | | | | | |
| Av. Sophistication of Broad Economic Category 21 Imports | UN, CEPII (BACI) | EU-28 countries | Industrial supplies not elsewhere specified, primary | Section 3.1 | 3 |
| Av. Sophistication of Broad Economic Category 22 Imports | UN, CEPII (BACI) | EU-28 countries | Industrial supplies not elsewhere specified, processed | Section 3.1 | 3 |
| Av. Sophistication of Broad Economic Category 41 Imports | UN, CEPII (BACI) | EU-28 countries | Capital goods (except transport equipment) | Section 3.1 | 3 |
| Av. Sophistication of Broad Economic Category 42 Imports | UN, CEPII (BACI) | EU-28 countries | Capital goods (except transport equipment), parts and accessories thereof | Section 3.1 | 3 |
| Share of foreign owned companies in Country (manufacturing) | BvD (AMADEUS) | EU-28 countries | based on employment share | Section 3.1 | 3,4 |
| Share of foreign owned companies in NACE2 per country | BvD (AMADEUS) | EU-28 countries | based on employment share | Section 3.1 | 3,4 |
| Share of foreign owned firms in NUTS2 region (manufacturing) | BvD (AMADEUS) | NUTS2 | based on employment share | Section 3.1 | 4 |
| Regional Heterogeneity and other Control Variables | | | | | |
| Employment | Cambridge Econometrics | NUTS2 | | Table 5.1 | 5 |
| Population Density | Eurostat | NUTS2 | Total population over land area | Table 5.1 | 5 |
| Compensation per Hour Worked | Cambridge Econometrics | NUTS2 | | Table 5.1 | 5 |
| Investment per Person Employed | Cambridge Econometrics | NUTS2 | | Table 5.1 | 5 |
| Manufacturing Employment Share | Cambridge Econometrics | NUTS2 | Share of total employment | Table 5.1 | 5 |
| Distance to the technological frontier | Regional Innovation Scoreboard | NUTS2 | Takes on values 0 (at frontier) to 3 | Table 5.1 | 5 |
| Degree of urbanisation | Eurostat | NUTS2 | Share of households in densely, inter- mediate or thinly populated areas | Table 5.1 | 5 |