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E-mail address: Andreas.Reinstaller@wifo.ac.at, Fabian.Unterlass@wifo.ac.at
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Medieninhaber (Verleger), Hersteller: Österreichisches Institut für Wirtschaftsforschung • 1030 Wien, Arsenal, Objekt 20 • Tel. (43 1) 798 26 01-0 • Fax (43 1) 798 93 86 • http://www.wifo.ac.at/ • Verlags- und Herstellungsort: Wien

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This paper presents an analysis of innovation behaviour at the firm level across countries with different levels of technological capabilities and economic development. Using data from the Community Innovation Survey for 20 European countries the paper shows that the impact of total innovation expenditures - including next to R&D also outlays for technology transfer, the market introduction of innovations or new designs - increases monotonically across countries with their level of technological capabilities. R&D investments instead have a significant impact on the generation of innovations only for firms located in countries with higher levels of technological capabilities. Firm specific competencies to suggest or contribute to innovation projects have a more significant effect on the innovation output the higher the level of economic development of the countries in which firms are located. Finally, the paper presents also evidence that R&D does not generally increase the absorptive capabilities of firms.

Address: Austrian Institute of Economic Research (WIFO), Arsenal Obj. 20, 1030 Vienna, Austria. E-mail: andreas.reinstaller@wifo.ac.at; fabian.unterlass@wifo.ac.at.

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1 Introduction

This paper presents an analysis of innovation behaviour at the firm level across countries. Using a large firm level data set it shows empirically how the opportunities to explore and exploit new technologies differ across countries with different levels of technological capabilities and economic development. Thereby it provides a firm level assessment on the factors driving technological convergence and divergence across countries.

Earlier studies have at first focused on differences in the levels of physical and human capital to explain diverging patterns of economic development and growth across countries mostly at the aggregate level (cf. Abramovitz 1986). Other contributions have invoked differences in domestic innovation efforts as a means to absorb foreign technology and engage into catching up (cf. Verspagen 1991, Fagerberg 1994) through imitation and technology diffusion to explain these differences. More recent studies have explored more thoroughly the factors driving economic growth closer to the technological frontier and have underscored the important effect higher education systems, education in general and the composition of human capital have on the generation of innovations (cf. Krueger and Kumar 2004, Aghion et al 2006). Several papers have also stressed the importance of competition, young firms and adequate financial institutions as important explanatory factors for the divergence of economic growth patterns across country (cf. Acemoglu et al 2006, Aghion and Howitt 2006).

Some authors have examined the impact of trade and foreign direct investment as determinants of economic growth across countries. Coe and Helpman (1995) or Keller (2002), for instance, have provided strong evidence for the important contribution of foreign R&D

to domestic productivity growth. Several other papers have instead established a link between variations in economic growth patterns across countries and the composition of the product basket of their exports (cf. Fagerberg et al 2007,Hausmann et al 2007, Saviotti and Frenken 2008) or the quality of products in these baskets (cf. Sutton and Treffler 2011).

Finally a number of contributions provide evidence for the importance of absorptive capacities to understand the differences in economic development and growth across countries. The notion of absorptive capacities is related to the idea that the implementation of new technologies depends as much on R&D as does the development of new innovations. Griffith et al (2006) for instance find using a panel of industries that R&D is important for technological catching-up as well as innovation, whereas Kneller and Stevens (2006) find that cross-country differences in the level of productivity depend more on the levels of human capital rather than the amount of R&D across industries. Kneller (2005) finally shows that absorptive capacities are important to absorb technological spillovers from foreign technology.

In this paper we examine the importance of R&D activities relative to other innovation activities related to technology transfer, the market introduction of innovations or new designs across groups of countries with different levels of technological capabilities and economic development at the firm level. We also provide evidence on how the importance and the impact of different sources of knowledge vary at the firm level across these country groups. The main data source for this study is the Community Innovation Survey, a standardised survey on innovation activities at the firm level, for 20 European countries. As other contribution have established a robust link between innovation and productivity using these data (cf. Abramovsky et al 2004, Griffith et al 2006) we focus on the production of innovations. We advance a small theoretical model to develop the hypotheses for this study.

2 Model

2.1 Innovation decision with two types of goods

The investment in R&D and other innovation assets of a firm depends on the (expected) returns these investments have for the firm. In order to analyse the innovation behaviour of firms across countries, derive hypotheses and interpret our quantitative results we adapt a model on the innovation investment decision of firms by Klette and Kortum (2004). Our model should be interpreted as capturing the behaviour of a representative firm in a country or group of countries with similar technological capabilities.

We assume that a firm produces two types of goods: The first type of goods are m new products, $m = 1, 2, 3, ...$, that represent leading edge innovations and are new to the market and give the firm a temporary monopoly position in that market. These products require knowledge of general principles and techniques that are commonly associated with science or with advanced engineering that is related to the generation of novel solutions and novel combination of different natural phenomena into a new product or technology. The second type of good, $n = 1, 2, 3, ...$, consists of products that represent an improved variety over some product that was already available in the market or a new product requiring a lower level of technological sophistication. Variables m and n count the products of the firm that have not yet been replaced through competition. The development and production of these products requires knowledge related to technical knowledge or technical skills that are typically associated with design and engineering activities dealing with the improvement of known technologies. We assume that with an innovation a firm can successfully replace an incumbent in the product's market. To produce a new good the firm has to invest into innovation activities.

Assume that these expenditures can yield an improvement to any of the m or n products with equal probability. Products of each type generate average profit of π_k, $k = m, n$, per product. If each good produces a unit revenue and if $0 < \pi_k < 1$ then the revenue for each product class is equal to k and the profit is equal to $\pi_k k$. The firm then receives profits the $\Pi = \pi_n n + \pi_m m$. For each product type there is a Poisson failure rate ϑ_k that indicates whether the firm's product (and hence its market) is replaced by a competitor. The firm then loses products at rate $\vartheta_k k$. New goods in class n or m are introduced through innovation investments and the firm's built up capability.

Klette and Kortum (2004) specify innovation investments through cost functions as follows:

$$R = \sum_k C(I_k, k). \tag{1}$$

These cost functions are assumed to be well-behaved insofar as C is strictly increasing in I_k/k, strictly convex and differentiable as well as homogeneous of degree one in these parameters. A simple functional form that satisfies these properties is then

$$R = \sum_k kc(I_k/\phi k) = \sum_k kc(I_k/\tilde{k}). \tag{2}$$

Equations (1) and (2) specify the total innovation expenditures of the firm. The parameter I_k is the Poisson arrival rate for one new invention in either product class. We assume also

$c(0) = 0$. The parameter ϕ, $\phi \in [0,1]$, is an index that captures the effect of the level of technological capabilities on the innovation output. Total innovation costs increase with this index.

The product portfolio of the firm $N = n+m$ changes by one unit given the Poisson arrival rates I_k and the failure rates ϑ_k. If the firm now tries to invest into innovation activities in order to maximise the firm value the intertemporal optimisation problem is given by

$$V(N) = \max_{I_k} \left\{ \sum_k (\pi_k k - R)\Delta t + \frac{1}{(1+r\Delta t)} E[V(N') \mid I_k] \right\}, \tag{3}$$

where N' captures the state of the firm after an arbitrarily small time step Δt. The change in value due to a change in market size of the firm during time step Δt is determined by

$$E[V(N') \mid I_k] = V(N) + \sum_k I_k \Delta t[V(N+1) - V(N)] - \sum_k \vartheta_k k \Delta t[V(N) - V(N-1)], \tag{4}$$

where the second term captures the change in value due to innovations and the third term captures the change in value due to the loss of market shares. The Bellman equation is then

$$\begin{aligned} rV(N) &= \\ &\max_{I_k} \left\{ \sum_k \pi_k k - \sum_k kc(I_k/\tilde{k}) + \sum_k I_k \Delta t[V(N+1) - V(N)] - \sum_k \vartheta_k k \Delta t[V(N) - V(N-1)] \right\}, \end{aligned} \tag{5}$$

where r is the discount rate of the firm. The first order conditions for the firm's optimal level of innovation investment are then

$$\tilde{c}'\left(\frac{I_m}{\tilde{m}}\right) = \tilde{c}'\left(\frac{I_n}{\tilde{n}}\right) = V(N+1) - V(N) \tag{6}$$

and the second order conditions are satisfied through the convexity assumptions made for the cost functions. Note that $\tilde{c}'(I_k/\tilde{k}) = \phi^{-1}c'(I_k/k)$, i.e. lower technological capabilities imply higher marginal costs. If the solution now is

$$\begin{aligned} V(N) &= vN, && (7)\\ I_m^* &= \mu_m^* m\phi^{\alpha} + I_m^{min} \rightarrow \tilde{I}_m^* = \mu_m^* \tilde{m} && (8)\\ I_n^* &= \mu_n^* n\phi^{\beta} + I_n^{min} \rightarrow \tilde{I}_n^* = \mu_n^* \tilde{n} && (9) \end{aligned}$$

given (7), (8) and (9), we can rewrite (6)

$$\tilde{c}'(\mu_m^*) = \tilde{c}'(\mu_n^*) = v \qquad \text{or} \qquad \tilde{c}'(0) > v \qquad \text{and} \qquad \mu_m^* \text{ and/or } \mu_n^* = 0 \tag{10}$$

where $\tilde{I}_k^* = I_k^* - I_k^{min}$, and α, β are the elasticities capturing the impact of knowledge quality on innovation productivity for which holds $0 < \alpha, \beta < 1$. I_k^{min} is a small autonomous probability of making a fortuitous innovation in product class k. The firm maximises then its discounted flow of revenues if the value of the innovation investment policy mix μ_m^* and μ_n^* equals

$$v = \frac{s_m[\pi_m - c(\mu_m^*)] + s_n[\pi_n - c(\mu_n^*)]}{r - s_m[\mu_m^* - \vartheta_m] - s_n[\mu_n^* - \vartheta_n]} \tag{11}$$

where $s_k = k/(m+n)$, is the share of firm sales in each product class.

Equation (11) now tells us, that a firm will choose the innovation investment intensities

μ_m^* and μ_n^* in such a way that the arrival rate of innovations for product classes m and n maximises the value of its flow of revenues. The value is increasing in π_k and decreasing in $r + \vartheta_k$. The solutions for the optimum innovation investment policies in equation (8) and (9) capture an important aspect of firm level innovation activities. In both equations the optimum level of innovation expenditures depends on the level of previous innovation investment and hence the capabilities accumulated through this as captured by the number of goods in each product class.

Total innovation expenditures are now given by

$$R^* = m^* c(\mu_m^*) + n^* c(\mu_n^*),$$

and the optimum innovation intensity is

$$\frac{R^*}{N} = s_m^* c(\mu_m^*) + s_n^* c(\mu_n^*). \tag{12}$$

To determine the composition of the product portfolio of the firm, consider that given the solution in equation (11) and the first order conditions in equation (10) the firm will chose the two product strategies m and n such that

$$\begin{aligned} s_m \frac{\pi_m - c(\mu_m^*)}{r - \mu_m^* + \vartheta_m} &\geq s_n \frac{\pi_m - c(\mu_m^*)}{r - \mu_m^* + \vartheta_m} \\ s_n \frac{\pi_n - c(\mu_n^*)}{r - \mu_n^* + \vartheta_n} &\geq s_m \frac{\pi_n - c(\mu_n^*)}{r - \mu_n^* + \vartheta_n}. \end{aligned} \tag{13}$$

The optimum composition of the firm's product portfolio/capabilities mix is therefore given by

$$s_m^* \quad = \quad s_n^* \frac{\pi_m - c(\mu_m^*)}{\pi_n - c(\mu_n^*)} \frac{r - \mu_n^* + \vartheta_n}{r - \mu_m^* + \vartheta_m}, \tag{14}$$

$$\text{with} \qquad s_m^* = 1 \quad \text{if} \quad \pi_n - c(\mu_n^*) = 0,$$

Figure 1 shows a situation on the unit simplex of product type shares where advanced R&D investments are more profitable to the firm relative to adoption and improvement investments. Starting from any point on the downward sloping line that captures combinations of shares s_n and s_m such that $s_n + s_m = 1$, the firm will ceteris paribus adjust its innovation investment through changes in μ_m^* and μ_n^*. As the process of increasing capabilities is discrete and stochastic the adjustment is sluggish and the shares s_m and s_n will gravitate toward point A in the figure gradually. Once the firm has reached this point it will invest just enough into innovation activities to keep its product portfolio balanced. Point A therefore represents a steady-state equilibrium for the firm.

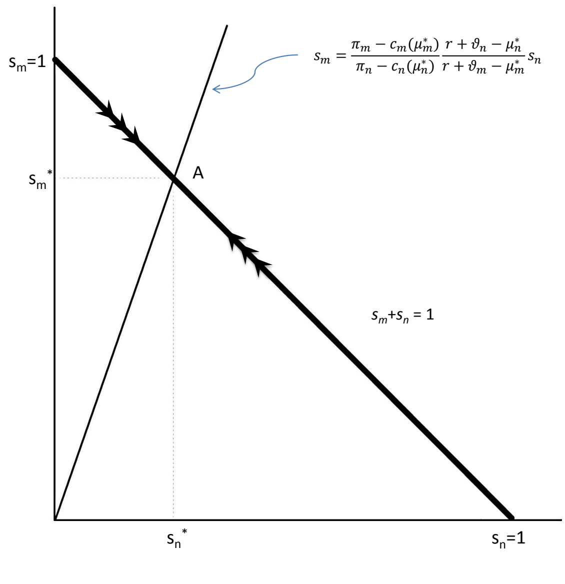

Figure 1: Equilibrium in the firm's product portfolio.

Given equations (11) and (14) the composition of the product portfolio of each firm, and hence the weight of its innovation investment, will be determined by the relative expected returns from each product policy. The overall innovation intensity of a firm, R/N shown in equation (12) therefore depends on the discounted returns on investments in advanced R&D relative to innovation investments related to the adoption and improvement of existing technologies.

2.2 Specialisation in innovation when technological capabilities and costs vary across countries

The considerations on the composition of a firm's product portfolio presented above can be extended to a case where two firms with different technological capabilities and cost structures operate in the same industry in which firms produce a variety of products covering different levels of technological sophistication. Leaving aside more subtle issues of competition such as innovation races, the aim here is to explain cross country differences in innovation strategies at the firm level. Therefore, we assume that the two firms are located in different countries and that they are representative for the average technological capability of the industry in their home country and that they compete in the same markets. We mark the foreign firm with '†'. If we further assume that the two firms are able to observe each others level of capabilities and cost structures then the two firms will adjust their product portfolio by taking into account their rival's traits. Differences in the cost structure are captured by π_k and $\pi_k^\dagger$, whereas differences in technological capabilities are captured by the shares s_k and $s_k^\dagger$. The optimum composition of the firm's product portfolio given the other firm's capabilities are then:

$$s_m^* = s_m^{\dagger *} \frac{\pi_m - c(\mu_m^*)}{\pi_m^\dagger - c(\mu_m^{\dagger *})} \frac{r - \mu_m^{\dagger *} + \vartheta_m^\dagger}{r - \mu_m^* + \vartheta_m} \quad \text{and} \quad s_n^* = s_n^{\dagger *} \frac{\pi_n - c(\mu_n^*)}{\pi_n^\dagger - c(\mu_n^{\dagger *})} \frac{r - \mu_n^{\dagger *} + \vartheta_n^\dagger}{r - \mu_n^* + \vartheta_n}. \tag{15}$$

Given the conditions for the optimum portfolio composition of the firm in equation (13) the result in equation (15) implies now that the product portfolio of both firms is optimal if

$$\frac{s_m^*}{s_n^*} = \frac{s_m^{\dagger *}}{s_n^{\dagger *}}, \tag{16}$$

and that the optimum product/capabilities portfolio of the firm as expressed in equation (14) is a best-response to the other firm's product/capabilities mix.

Figure (2) shows a case where the second firm has a comparative advantage in products related to technology adoption and innovations improving existing products and technologies.

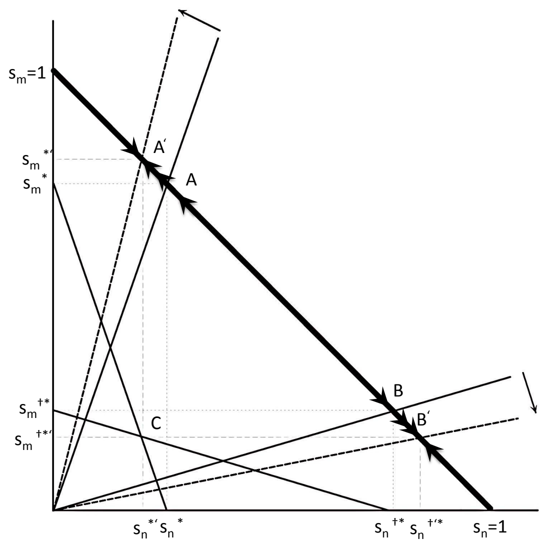

Figure 2: Equilibrium in the firm's product portfolio with international competition in two product classes in an industry with different cost structures and technological capabilities.

The two firms will mutually adjust the composition of their product portfolios in line with the condition in equation (16) that is shown in the figure as point C. The composition of the product portfolio of the first firm will now gravitate towards point A', whereas the composition of the product portfolio of the second firm will move towards point B'. In other words, the first firm specialized in technologically more sophisticated products whereas the second specializes in technologically less sophisticated ones.

This analysis shows that the firm with higher technological capabilities will give up market shares in technologically less sophisticated products, whereas the firm with lower technological capabilities will acquire shares in this product category and give up markets in the most advanced markets in the industry. Given equation (2) this implies that the more advanced firm has an incentive to increase the share of innovation investments it spends on R&D activities in order to compensate for potential loss in the market segments with lower quality, whereas technologically less advanced firms will focus their innovation activities on the adoption and improvement of existing technologies. Given the technological capabilities of their technologically more advanced competitors their incentive to invest into R&D is more limited. As a consequence a specialization emerges within an industry determined by the distribution of capabilities across firms and countries.

2.3 Implications for the empirical analysis

The analysis in the previous section suggests that firms operating in a country with on average higher technological capabilities will allocate more resources to the development of technologically more sophisticated products to maximise the value of their discounted flow of profits. The technological capabilities will be viewed here as the internal and external resources upon which a firm can draw when it creates or absorbs new knowledge.

A firm that can draw on better technological capabilities will have cost advantages in the generation of new innovations as captured by the marginal productivity of innovation investments, $\tilde{c}'(\mu_k^*) < \tilde{c}'(\mu_k^{*\dagger})$. Increments in innovation investments will therefore have a higher impact on the innovation output for firms with higher technological capabilities.If these capabilities vary systematically across countries, then we should observe that increments in innovation investments have a higher impact on innovation output on average at the firm level in countries with higher technological capabilities.

Innovation output consists of both new m type and n type products. In order to test whether firms located in countries with higher technological capabilities are also more productive in the generation of R&D intensive m-type goods, we have to disentangle the impact of changes in R&D investment on innovation output from the impact of total innovation investment. We approach this goal stepwise and look at the impact of R&D on innovation output first:

> *Hypothesis I: The impact of an increase in the share of R&D investment in total innovation expenditures on innovation output will on average be higher for firms operating in countries with higher levels of technological capabilities.*

Total innovation investments comprise next to R&D outlays also costs incurred for the adoption and adaptation of new technologies such as license fees, expenditures for product design, training and so forth. As firms in countries with higher technological capabilities should also be more productive in innovation activities requiring generally lower levels of technological capabilities, we generalise Hypothesis I:

> *Hypothesis II: The impact of an increase in total innovation investments at the*

firm level will on average increase for firms operating in countries with higher levels of technological capabilities.

In order to establish to what extent R&D investments drive the impact of total innovation investment on innovation output or whether other types of expenditures cause this effect we test an additional hypothesis. Under realistic assumptions the analytical results presented in Figure (2) indicate that we should expect that increases in R&D investment will have a higher impact on the innovation output of firms in countries with higher technological capabilities:

- Firms have ceteris paribus an incentive to increase innovation intensity μ to escape competition, but only to the extent that increased costs for innovation activities are compensated through increases in the discounted value of output. If higher technological capabilities imply higher research productivity this strategy to escape competition is more valid to firms in with (on average) higher technological capabilities than competitors in the same industry. These firms have therefore an incentive to increase innovation investments. This incentive is enforced if imitation is easier for technologically less sophisticated n-type of products. In this case competition will be higher in these markets.
- If technologically more advanced products not only require more research investments but command also a price premium such that $\pi_m > \pi_n$, firms in countries with higher technological capabilities will have an incentive to engage into innovation investments related to this type of products as they increase the value of the discounted flow of profits.

- If countries with higher levels of technological capabilities have ceteris paribus cost disadvantages in the production of lower quality products due to higher factor costs, $\pi_n < \pi_n^{\dagger}$ then firms in these countries have an incentive to give up production of these goods.

From these observations follows:

> *Hypothesis III: The impact of a change in innovation investment on the innovation output is higher for firms that increase the share of R&D outlays in total innovation investments only in the technologically most sophisticated countries.*

Hypothesis III has also to be viewed in the light of prior findings on the capabilities to absorb technologies at the firm level. It has been suggested that the absorption of technology created by others requires firms to devote research efforts and resources to the understanding of earlier technology in order to better handle present day technology and speed up adoption. R&D expenditures have been identified as an important factor affecting absorptive capacities, i.e. the capability to adopt new technologies. This implies that there is a conditional element linking R&D investment to other types of innovation investments insofar as the former is thought to foster the latter. From a confirmation of Hypothesis I and II we should expect that in less developed countries R&D investments may not have a direct strong impact on innovation output, but it may have a mediating effect through its interaction with the level of total innovation investment. Hence, for firms in economically and technologically less developed countries R&D investments should have a positive impact on innovation output through their positive impact on all other types of innovation investment. However, the reverse argument may also be true. If knowledge is cumulative then certain levels of technological investment have to be reached in order to be able to successfully engage into technologically more advanced research and development activities. We should then expect that the conditional effect between R&D investment and the level total innovation investment is observable only in the countries specialising into technologically more advanced products. From our model we draw the conclusion that the postulated interdependence between R&D and other types of innovation investment should be observable only for the economically and technologically most advanced economies, as only in these countries firms should be able to draw additional value from these activities. We therefore offer a more differentiated view on the issue of technology absorption.

The final question explored in this paper focuses on the type of knowledge sources upon which firms draw to start or implement innovation projects and what impact they have on the innovation output at the firm level. The literature reviewed in the introduction of this paper suggests that there are several transmission channels through which knowledge crucial for successful innovation finds its way into firms. Next to investments into technology absorption these are

- human capital,
- knowledge acquired through research cooperations, and
- competition as well as interaction with user on the market.

Higher technological capabilities at the firm level should support the translation and absorption of information derived from these sources into successful innovation. Hence, firms located in countries with higher technological capabilities should on average also be better able to absorb knowledge from different knowledge sources relative to firms operating in less advanced countries. From this follows:

Hypothesis IV: The impact of using internal and external knowledge sources to develop and implement innovation projects on innovation output will be higher for firms located in countries with higher technological capabilities relative to firms located in countries with lower levels of technological capabilities.

3 Data and methodology

3.1 Data sources

The Community Innovation Survey (CIS) is a standardised survey carried out in 27 EU Member States and three associated countries. The CIS is designed to obtain statistically representative information on innovation activities within companies, as well as on various aspects such as the effects of innovation, sources of information used, costs, hampering factors etc. that is also comparable across countries. Since 2004 a full CIS survey is carried out every four years and a reduced survey every two years after a full survey. The last survey has been carried out in 2010.[1]

The empirical analysis in this paper uses data of the third wave of the Community Innovation Survey (CIS), which covers the period 1998-2000. The data set that was available for this study covers 20 countries: Belgium (BE), Bulgaria (BG), Czech Republic (CZ), Denmark (DK), Estonia (EE), Finland (FI), Germany (DE), Greece (GR), Hungary (HU), Iceland (IS), Italy (IT), Latvia (LV), Lithuania (LT), Luxemburg (LU), Portugal (PT),

[1]For detailed information on the CIS see `http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/en/inn_esms.htm`.

Romania (RO), Slovakia (SK), Slovenia (SI), Spain (ES) and Sweden (SE). Company level data for these countries were accessed at the Eurostat safe centre in Luxemburg. It was possible to pool these data. The sample comprises 70924 firms with a nonzero share of sales from innovative products. The reason for using the CIS 3 data set and not more recent waves of the CIS is that only the CIS 3 covers information on the export intensity of firms, which is an important aspect to control for in cross country comparisons of innovation performance.

A general limitation of the CIS is that many of the data collected in this survey reflect the individual firms' own assessment of their innovation activities. These subjective assessments may be biased and for this reason the data are rather noisy especially for questions where it is hard to define an objective standard for measurement. The CIS data are also only available as a cross-section and therefore provide information on innovation expenditures only at some specific point in time for different types of innovation activities including both R&D and other innovation investments.It is not possible to infer the overall level of capabilities in terms of 'knowledge capital' stocks. Finally, there is also little information on the competitive situation of the firm, the composition of the work force and other important parameters considered, for instance, in the model by Acemoglu et al (2006), which could not be tested with CIS data.

3.2 Econometric issues

The principal dependent variable – the share of turnover from new to market products, $s_{I,i}$ – is a fraction bounded between zero and one by definition. For this type of share equation Papke and Wooldridge (1996) have proposed the so called fractional logit model,

$$E(s_{I,i} \mid \mathbf{x}_i) = G(\mathbf{x}_i\beta),$$

where $G(\cdot)$ is a (non-linear) function satisfying that the predicted variables will lie in the interval $[0,1]$ and $\mathbf{x}_i$ and β are the vectors of independent variables and coefficients respectively as presented in equations (18) through (21). The most popular function for $G(\cdot)$ is the logistic function,

$$G(\mathbf{x}_i\beta) \equiv \frac{\exp(\mathbf{x}_i\beta)}{1+\exp(\mathbf{x}_i\beta)}, \tag{17}$$

for which the Bernoulli log-likelihood function is

$$l_i(\beta) = s_{I,i}\log[G(\mathbf{x}_i\beta)] + (1-s_{I,i})\log[1-G(\mathbf{x}_i\beta)],$$

and from which a quasi-maximum likelihood estimator with heteroscedasticity robust asymptotic variance of β can be obtained which is consistent.

In the CIS non-innovative firms are routed around the questions on the innovation input. However, a restriction of the estimates to the selected (innovative) sample would imply biased estimates. In order to obtain unbiased estimates we use the Heckman two-step estimator (Heckit) to control for sample selection issues (see e.g. Vella 1998, Puhani 2000). As we are interested in estimating the innovation production functions given by equation (18) through (21) the first stage is a probit selection equation that describes the propensity to innovate d^* with the associated indicator function d_i

$$d_i^* = \mathbf{z}_i'\gamma + \nu$$

$$d_i = \begin{cases} 1 & \text{if } d_i^* > 0 \\ 0 & \text{if } d_i^* \leq 0, \end{cases}$$

To correct for the fact that $E(\varepsilon_i \mid \mathbf{z}_i, d_i = 1) \neq 0$ we estimate the selection equation using the entire sample and construct from this the inverse Mills ratio λ_i which is included as an explanatory variable in the innovation output equation which is estimated only for the firms where data on innovation input data are available. Variable ε_i is the error term of $G(\cdot)$ in equation (17). The variables used in the estimation of the selection equation have already been described earlier. The selection model therefore consists of a probit equation in the first stage and a fractional logit model in the second stage.

Finally, we have estimated the sample selection models weighting the regressions with the sample weights. As the national CIS samples of companies are stratified by sector of activity and size-classes, the statistical offices provide the correct sample weights. These factors are generally based on the total number of enterprises/employess in each stratum of the frame population divided by the number of the realised sample. As our paper aims at making general statements on differences in innovation behaviour of firm populations across countries using these weights ensures that the analysis provides the needed link between the observations from a probability sample of enterprises and population parameters about the enterprise population. In addition it allows us to correct for different sample sizes when we pool CIS samples for different countries. Sensitivity analyses carried out using weighted and unweighted regressions show that the overall results hold even though the differences in impact of the variables of interest become slightly less accentuated especially for the country groups with intermediate technological capabilities.

3.3 Country groups

In order to analyse systematic differences in the production of innovations at the firm level across countries with different levels of technological capabilities in the business sector, we construct a classification that classifies countries on the basis of their technological capabilities and their level of economic development. For each of these country groups we estimate then identical econometric models for innovation production functions at the firm level on the pooled subsamples to assess whether the technological determinants of innovation output differ systematically across groups.

The classification has been built using an average linkage cluster algorithm and the Euclidian distance as dissimilarity measure. We have used real GDP per capita at purchasing power parities from the Eurostat database as well as data on direct and indirect R&D embodied in imported and domestic capital goods and inputs provided by Knell (2008) on the basis of an analysis of sectoral R&D data using linked national input-output tables to group the countries. These data capture the average technological capabilities of the business sector in each country in terms of the capability to create new technological knowledge (direct R&D) and in terms of the capability to absorb new technology (R&D embodied). All variables have been standardised with regard to their sample means. Romania, Luxemburg and Iceland have been allocated to groups based on the results of an R&D decomposition analysis presented in Reinstaller and Unterlass (2012). For these countries Knell (2008) provides no data. This cluster analysis has led to the following four country groups listed in the order of their levels of technological capabilities:

Country group 1: Finland (FI) and Sweden (SE), Belgium (BE), Denmark (DK), Iceland (IS), Luxemburg (LU) and Germany (DE);

Country group 2: Estonia (EE), Czech Republic (CZ), Slovakia (SK), Slovenia (SI) and Hungary (HU);

Country group 3: Italy (IT), Spain (ES), Portugal (PT) and Greece (GR);

Country group 4: Bulgaria (BG), Romania (RO), Latvia (LV) and Lithuania (LT).

Country group 1 assembles the economically most advanced economies in the sample with high levels of direct and indirect R&D intensity. Country group 2 and country group 4 pool Eastern European countries where the countries in group 2 are economically more advanced with higher technological capabilities, whereas the countries in group 4 trail the other countries in the sample in terms of economic development and technological capabilities. The countries in group 2 are on a distinct catching up trajectory. The countries in group 3 have real GDP per capita levels that are higher than that of country groups 2 and 4 and close to that of country group 1 but the levels of direct and indirect R&D intensity are lower due to their industry structures that are dominated by sectors in the low and medium technology segments.

3.4 Variable definitions

As we use two stage sample selection models to explore the hypotheses advanced earlier we have to use two partly disjoint sets of variables in order to correctly instrument the outcome equation of interest in the second stage.

Table 1 about here.

Table 1 lists the variables that will be used in this paper for different specifications of the outcome equation. They are defined as follows:

- The **new-to-market product share** (s_I) represents the share of turnover that arises from the sale of products considered to be new to the market by the firm. This variable is directly available in the CIS dataset under the name 'turnmar' and it refers to the year 2000. It is used as LHS variable for all models explored in this paper as the value of innovations cannot observed directly and because it captures successful innovation activities and innovation output. As a share variable it is bounded between 0 and 1. Table 1 also shows that this indicator in the range between 3 and 5% across country groups. New-to-market products are not necessarily related to prior R&D activities but they are meant to capture innovations that are not pure imitations. For this the CIS offers a another variable. We have calculated also a variable that combines these two indicators. As the results remain essentially the same we have opted to use the original CIS indicator in the presentation and discussion of the results.

- The **share of R&D in total innovation expenditure** (SRDTIE) has been calculated on the basis of expenditures for internal ('rrdinx') and external ('rrdexx') R&D in total innovation expenditures ('rtot') in the year 2000. The abbreviations under quotation marks correspond to the variable names used in the harmonised CIS questionnaire. Table 1 indicates that this variable varies considerably across country groups. It is on average highest in country group 1 with about 26.7% and lowest in country group 4 with 3.5%.

- The **innovation intensity** (INNOVI) has been calculated as share of total gross innovation expenditures ('rtot') in turnover ('turn') in the year 2000 and ranges between 3.2% and 1.4% on average across country groups. The variation inside each country group is considerable and it can go up to four times the turnover of a firm. The maximum values for this indicator typically apply to technology intense start-ups with a high level of external financing. Note that the variable captures gross investments. It is therefore closely correlated to unobserved stocks of intangible capital accumulated by the firm.

- The **employment intensity** (EMPI) is expressed as the number of employees ('emp') in year 2000 per 1000 € turnover ('turn') in year 2000. This variable is the inverse of labour productivity.
- The **investment intensity** (INVI) captures gross investments into tangible assets in year 2000 ('invta') as share of total turnover in year 2000 ('turn'). This variable is a proxy for the capital stock as it represents gross investments and therefore controls also for the capital intensity of the firm. As it is not possible to impute the share of investments needed to produce innovations only, we should expect that the estimated coefficients for this variable will only be weakly significant.
- The indicator variable **start-ups** ($d_{startup}$) is a dummy for newly established firm ('est'). It controls for the high shares of new to market products newly established firms typically report.
- The **log turnover** (TURN) has been calculated from the turnover in year 2000 ('turn'). It controls for the firm size.
- The **export intensity** (EXPI) has been calculated from total exports in goods and services ('exp') and refers to the year 2000. This variable controls for the exposure

of the firm to international competitors.

- The **importance of knowledge sources internal to the firm for innovation** (SI) has been calculated from a set of questions in the CIS asking for the 'main sources of information needed for suggesting new innovation projects or contributing to the implementation of existing projects'. Firms had to indicate the degree of importance attached to various alternative information sources on a scale with the options 'high', 'medium', 'low' and 'not used'. We have assigned to each of these options the values 3, 2, 1 and 0, respectively. Variable SI is then defined as the maximum value assigned to any of the different types of company specific knowledge sources (own enterprise, 'sent', own enterprise group, 'sgrp'). As a consequence variable SI is bounded between 0 and 3. Table 1 shows that these types of knowledge sources are rated as most important in country group 1 and least important in country group 4. As knowledge sources internal to a firm are related to its own capabilities that in turn are to a large extent also embodied in individuals the variable captures the transmission of knowledge from the education sector to the business sector as well as the capability of the firm to create own knowledge.

- The indicator on the **importance market related knowledge sources for innovation** (SM) has been constructed in an identical fashion as variable SI. In this case it comprises the importance of market related information sources such as suppliers ('ssup'), customers ('scli'), and competitors ('scom').

- The variable **importance of research institutions as knowledge sources for innovation** (SPR) reflects the importance firms have attached to public research institutions (universities, 'suni', governmental research laboratories, 'sgmt') as a source of knowledge for new innovation activities.

- The variable representing the **basicness of R&D conducted by the firm** (BASICNESS) has been constructed with the aim to capture the importance of scientific knowledge and advanced research for the innovation activities of a company. It is a dummy variable that equals 1 if a company has indicated to invest continuously either into internal or external R&D and if it has either cooperated with public research laboratories or universities or used one of them as innovation source. The reasons for including this variable is that some authors have argued that the importance of advanced research and scientific research for innovation increases the closer firms are to the technological frontier (see e.g. Aghion and Howitt 2006). This variable therefore tries to capture the direct channel of knowledge transmission that links research institutions to companies through research cooperations and the exchange of knowledge.

Table 2 about here.

The two key variables of interest in this analysis are the share of R&D in total innovation expenditures, SRDTIE, and the innovation intensity, INNOVI. A correlation analysis (Table 2) for the pooled sample shows that they are only weakly correlated. The control variables are also only weakly correlated with the other variables. Multicollinearity should therefore not represent a major issue of concern in the baseline models presented later. Things are slightly different for the indicators capturing the importance of different types of knowledge sources (SI, SM, SPR, BASICNESS) are more heavily correlated among one other and with SRDTIE. For this reason we will estimate two alternative models in which these indicators will be used.

As the Heckman two-stage estimator does not perform well when the degree of collinearity between the outcome and the selection equations is high, we have used a largely different set of explanatory variables to model the propensity to innovate in the selection equation:

- The dependent variable d_i is equal to 1 if a firm has indicated to have introduced new or significantly improved products ('inpdt') or processes ('inpcs') or if it had ongoing innovation activities ('inon') in the period 1998-2000. The indicator is zero if none of these conditions is met. The abbreviations under quotation marks correspond again to the variable names used in the harmonised CIS questionnaire.
- The selection equation shares the variables EMPI, INVI, TURN, EXPI and $d_{startup}$ with the outcome equations. These variables control for key characteristics of the firm.
- The selection equation includes dummies capturing different types of investment pertinent to innovation activities:
  - internal R&D ('rrdin'),
  - external R&D ('rrdex'),
  - acquisition of machinery and equipment ('rmac'),
  - acquisition of external knowledge such as licenses ('roek'),
  - training activities ('rtr'),
  - investments related to the market introduction of innovations ('rmar'), and
  - outlays for procedures and technical preparations to realise the actual imple-

mentation of products ('rpre').

- In addition a dummy was also included indicating whether a firm performs R&D on an ongoing basis or not.

- Following Peneder (2010) we have included indicators that capture the appropriability and cumulativeness of knowledge as experiences by the individual firm in order to capture important aspects of technological regimes in which firms operate. These variables can be constructed from the CIS data.

- The selection equation included also three dummy variables on different types of organisational innovation in

  - strategy, management or organisation ('actstr', 'actman', actorg'),
  - marketing ('actmar'), and
  - aesthetic changes to products ('actaes').

- Finally, we have included also country and sector dummies in the selection equation.

3.5 The empirical models

In order to estimate the outcome equation of the sample selection model, we take a standard production function framework as a starting point to model the output of new to market innovations through labour, capital and knowledge capital inputs. In order to take into account the specifics of the data it is necessary to transform it into a share equation, where all variables are expressed in relation to total sales.[2] Taking into account necessary controls the baseline econometric model can then be specified as

[2] See the appendix for the derivation of the share equation underlying the econometric models estimated in this paper.

$$
\begin{aligned}
E(s_{I,i} \mid \mathbf{x}_i) \quad = \quad & G(\alpha_i + \beta_1 \mathrm{EMPI}_i + \beta_2 \mathrm{INVI}_i + \beta_3 \mathrm{SRDTIE}_i + \beta_4 \mathrm{INNOVI}_i + \beta_5 \mathrm{EXPI}_i + \beta_6 \log(\mathrm{TURN})_i + \\
& + \beta_7 \mathrm{d}_{startup,i} + \sum_{k=1}^{20} \beta_{country,l} \mathrm{d}_{country} + \sum_{l=1}^{41} \beta_{sector,k} \mathrm{d}_{sector} + \beta_8 \lambda_i + \varepsilon_i). \qquad (18)
\end{aligned}
$$

The key variables in this equation are the innovation intensity (INNOVI_i) and the share of R&D in total innovation expenditures (SRDTIE_i). This specification has a number of advantages: we avoid collinearity issues between innovation and R&D intensity, we are able to capture the importance of R&D vis-a-vis other types of innovation expenditures, and in doing so we control also for the level of total innovation expenditures. Variable EMPI_i is the inverse of productivity and therefore captures key aspects of firm performance, whereas EXPI_i is the export share and therefore controls for the exposure of the firm to international competitors. Variable INVI_i represents in turn the investment intensity of the firm, and λ_i captures the inverse Mills ratio correcting for the sample selection bias. The index i runs over all firms in the sample. It should be noted that variables INVI_i and INNOVI_i are not stock variables. The CIS data do not allow us to calculate stocks of tangible or intangible capital. However, both variables capture gross investment expenses and therefore comprise scrapping which is in turn closely related to the related stock variables. Hence, it can be shown that the estimated coefficients will also capture the size effect of the stock variables. On the other hand, as the capital investment variable INVI_i cannot be imputed to the share of turnover from new to market products the estimated coefficients should be small but significant. With the first model we assess Hypotheses I and II.

In order to explore the interaction between total innovation expenditures (INNOVI_i) and the share of R&D in total innovation expenditures we expand equation (18) with the interaction term, $\text{SRDTIE}_i \times \text{INNOVI}_i$, to yield

$$\begin{aligned} E(s_{I,i} \mid \mathbf{x}_i) &= G(\alpha_i + \beta_1 \text{EMPI}_i + \beta_2 \text{INVI}_i + \beta_3 \text{SRDTIE}_i + \beta_4 \text{INNOVI}_i + \beta_5 (\text{SRDTIE}_i \times \text{INNOVI}_i) + \beta_6 \text{EXPI}_i + \\ & + \beta_7 \log(\text{TURN}_i) + \beta_8 \text{d}_{startup,i} + \sum_{k=1}^{20} \beta_{country,l} \text{d}_{country} + \sum_{l=1}^{41} \beta_{sector,k} \text{d}_{sector} + \beta_9 \lambda_i + \varepsilon_i). \end{aligned} \tag{19}$$

Clearly, the interaction term yields the R&D intensity of the firm. The evaluations based on this model will be used to assess Hypotheses II and III.

Finally we explore the role of knowledge sources we expand the model in equation (18) with the indicators capturing the importance of different types of knowledge sources for firms,

$$\begin{aligned} E(s_{I,i} \mid \mathbf{x}_i) &= G(\alpha_i + \beta_1 \text{EMPI}_i + \beta_2 \text{INVI}_i + \beta_3 \text{SRDTIE}_i + \beta_4 \text{INNOVI}_i + \beta_5 \text{EXPI}_i + \\ & + \beta_6 \log(\text{TURN})_i + \beta_7 \text{d}_{startup,i} + \beta_8 \text{SI}_i + \beta_9 \text{SM}_i + \beta_{10} \text{SPR}_i + \\ & + \sum_{k=1}^{20} \beta_{country,l} \text{d}_{country} + \sum_{l=1}^{41} \beta_{sector,k} \text{d}_{sector} + \beta_{11} \lambda_i + \varepsilon_i) \end{aligned} \tag{20}$$

and the alternative model

$$\begin{aligned} E(s_{I,i} \mid \mathbf{x}_i) &= G(\alpha_i + \beta_1 \text{EMPI}_i + \beta_2 \text{INVI}_i + \beta_3 \text{SRDTIE}_i + \beta_4 \text{INNOVI}_i + \beta_5 \text{EXPI}_i + \beta_6 \log(\text{TURN})_i + \\ & + \beta_7 \text{d}_{startup,i} + \beta_8 \text{BASICNESS}_i + \sum_{k=1}^{20} \beta_{country,l} \text{d}_{country} + \sum_{l=1}^{41} \beta_{sector,k} \text{d}_{sector} + \beta_9 \lambda_i + \varepsilon_i) \end{aligned} \tag{21}$$

to capture the importance of knowledge sources that are more likely related to leading edge scientific research. In the model in equation (20) we are particularly interested in the variables capturing the impact of internal knowledge sources (SM_i) and the public research institutions (SPR_i). The variable capturing the market in terms of competitors or users as a knowledge source (SM_i) has been included as a control. The model in equation (21) instead uses the variable $BASICNESS_i$ that aims at capturing to what extent to what extent the R&D carried out by the firm is related to leading edge research. As this variable is collinear with other indicators for knowledge sources it is included in a separate model. These two models will be used to explore Hypothesis IV.

4 Results

The regression tables presented in this section report average marginal effects. For the sake of brevity we omit a detailed description of the first stage selection equation. The estimated coefficients for the inverse Mills ratio λ_i are significant at the 1% level and negative in all but two cases. The correlation of the predicted errors of the selection equation and the second stage equations (Rho) reported in the tables as well as the associated p-values, p(Rho), confirm the existence of a selection bias.

Table 3 about here.

Table 3 presents the results for the first model in equation (18) for the pooled sample and for the four country groups. Looking at the controls first we see that the marginal effects of the export intensity (EXPI), the log turnover (TURN), and start-ups ($d_{startups}$) for the pooled sample are significant at the 1% level and show all the expected sign. Across country groups the marginal effects of log turnover are all highly significant and negative. For the export intensity they are statistically significant only for country group 3, and for start-ups they are significant and positive only for country groups 1 and 3 indicating that start-ups are more innovative in these country groups. Being a start-up in country group 1 is associated with an higher share of turnover from new to market innovations of about 2.4 percentage points. The impact of changes in employment intensity (EMPI) is negative and significant at the 10% level in the pooled sample as expected. The statistical significance is at the 1% level for the subsamples of country groups 1, 2 and 4. In all cases the results for this variable show that a fall in productivity is associated with a decline in innovation output. The impact of employment intensity is however largest with a considerable margin in country group 1. The marginal effect for the investment intensity (INVI) is in turn statistically not significant for the pooled sample, whereas for country groups 1 and 2 it is significant at the 5% level and positive. Overall these results indicate that the controls capture important parts of the variation in the dependent variable.

With the baseline model in equation (18)we test the first two hypotheses, which postulate that the impact of an increase of total innovation investments (Hypothesis I) as well as the impact of increases of the share of R&D investment in total innovation expenditures (Hypothesis II) on the innovation output will be higher in countries with a higher level of technological and economic development. The variables of interest to test these two hypotheses are INNOVI and SRDTIE.

In the pooled sample the marginal effects for both indicators are positive and significant at the 1% level. The marginal effects for an increase of the innovation intensity, INNOVI, are also positive and statistically significant across country groups. An increase of the innovation intensity by 10 percentage points increases the share of turnover from new to market products by approximately 0.85 percentage points in country group 1 and by about 0.25 percentage points in country group 4 on average across firms. The marginal effects for an increase in the share of R&D in total innovation expenditures on innovation output are positive and significant only for country groups 1 and 2, and insignificant for country groups 3 and 4 on average across firms. The marginal effect in country group 1 is also about three times larger than in country group 2. In order to test whether the observed differences in the estimated average marginal effects across country groups are statistically significant, we have carried out a two-sample mean-comparison t-test with unequal variance for both variables across country groups in pairwise comparisons.[3] The results of the pair wise group comparisons in Table 4 indicate that the marginal effects of both SRDTIE as well as INNOVI on the share of turnover from new-to-market innovations are statistically significant across country groups. These results therefore lend support to Hypotheses I and II: Changes in innovation intensity and in the share of share of R&D in total innovation expenditures have a higher impact on average for firms located in countries with a more advanced level of technological development. R&D activities seem also to have an impact in countries with higher technological capabilities only.

Next we examine whether the impact of total innovation expenditures on innovation output is conditional upon changes in the share of R&D investments in total innovation investments. The underlying hypothesis is that the impact of innovation investments on innovation output is higher in countries with higher technological capabilities in the business sector if the share of R&D in total innovation investment increases as well (Hy-

[3]The test statistic is defined as $t = \frac{\hat{b}_{ij} - \hat{b}_{ik}}{\sqrt{s^2_{\hat{b}_{ij}}/n_{\hat{b}_{ij}} + s^2_{\hat{b}_{ik}}/n_{\hat{b}_{ik}}}}$, where i refers to the observation for which the marginal effect was estimated and j and k denote the country groups that are compared. $\hat{b}_{ij}$ and $\hat{b}_{ik}$ represent the estimated marginal effects with standard errors $s_{\hat{b}_{ij}}$ and $s_{\hat{b}_{ik}}$ as well as observations $n_{\hat{b}_{ij}}$ and $n_{\hat{b}_{ik}}$. The result is distributed as Student's t with v degrees of freedom, where v is calculated following Satterthwaite's formula.

pothesis III). Hence, keeping the level of R&D expenditures at zero, the impact of an increase in innovation investments should first increase across countries the higher their level of technological and economic development and decrease again for the countries with the highest levels of technological capabilities.

With the model in equation (19) we infer on how the effect of the innovation intensity on the share of turnover from new to market products depends on the share of R&D expenditures in total innovation expenditures, i.e. we test a hypothesis about an interaction term in a nonlinear model (cf. Ai and Norton 2003). The correct partial effects for the logit function in equation (17) for variables INNOVI and SRDTIE taking into account the interaction effect are then

$$\frac{\partial s_{I,i}}{\partial INNOVI_i} = (\beta_4 + \beta_5 SRDTIE_i) * \frac{\exp(\mathbf{V}_i)}{(1+\exp(\mathbf{V}_i))^2} \tag{22}$$

$$\frac{\partial s_{I,i}}{\partial SRDTIE_i} = (\beta_3 + \beta_5 INNOVI_i) * \frac{\exp(\mathbf{V}_i)}{(1+\exp(\mathbf{V}_i))^2}, \tag{23}$$

where $\mathbf{V}_i = \mathbf{x}_i\beta$ in equation (19). Clearly, these marginal effects can be nonzero and are determined by all covariates of the observed firm even if $\beta_5 = 0$. As statistical tests about partial effects for interacted regressors in nonlinear models are not informative (see Greene 2010), we plot only the estimated marginal effects in equations (22) and (23) for each observation in the pooled sample as well as in the different subsamples. The graphical representation shows the magnitude of the partial effects of one variable on the outcome variable taking into account the interaction effect for different levels of the other interacted dependent variable.

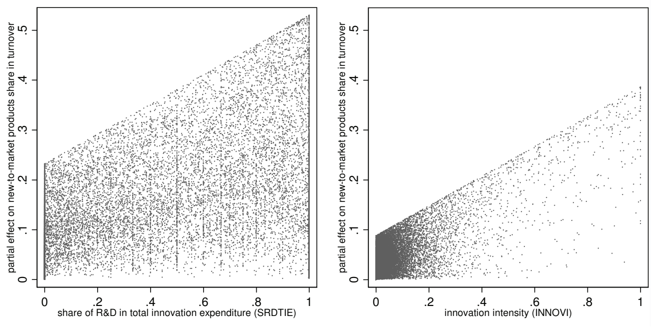

Figure 3: Partial effects for the interaction term between the innovation intensity (INNOVI) and the share of R&D in total innovation expenditures (SRDTIE) on the share in turnover from new to market products (s_I) for the pooled sample. The plot for equation (22) for changing SRDTIE is shown left; the plot for equation (23) for changing INNOVI is on the right.

Figure (3) shows the partial effects for the pooled sample. It presents the estimated marginal effects of the innovation intensity (INNOVI) on the innovation output variable in the left panel and those for the share of R&D in total innovation expenditures in the right panel. The left panel of the plot reveals that the impact of an increase of the innovation intensity on the innovation output variable increases for firms with higher shares of R&D expenditures in total innovation outlays. The right panel instead shows that the positive impact of changes in R&D on the innovation output increases also for firms that invest a higher share of their turnover for innovation investments.

The evidence presented in Figure (3) indicates that a strong R&D capability is essential for firms to become more innovative across all countries. A break down of this result reveals however, that this conclusion cannot be generalised in this way.

In Figure (4) we plot the estimated marginal effects of the innovation intensity (INNOVI) on the innovation output variable for the four country groups. The marginal effects are

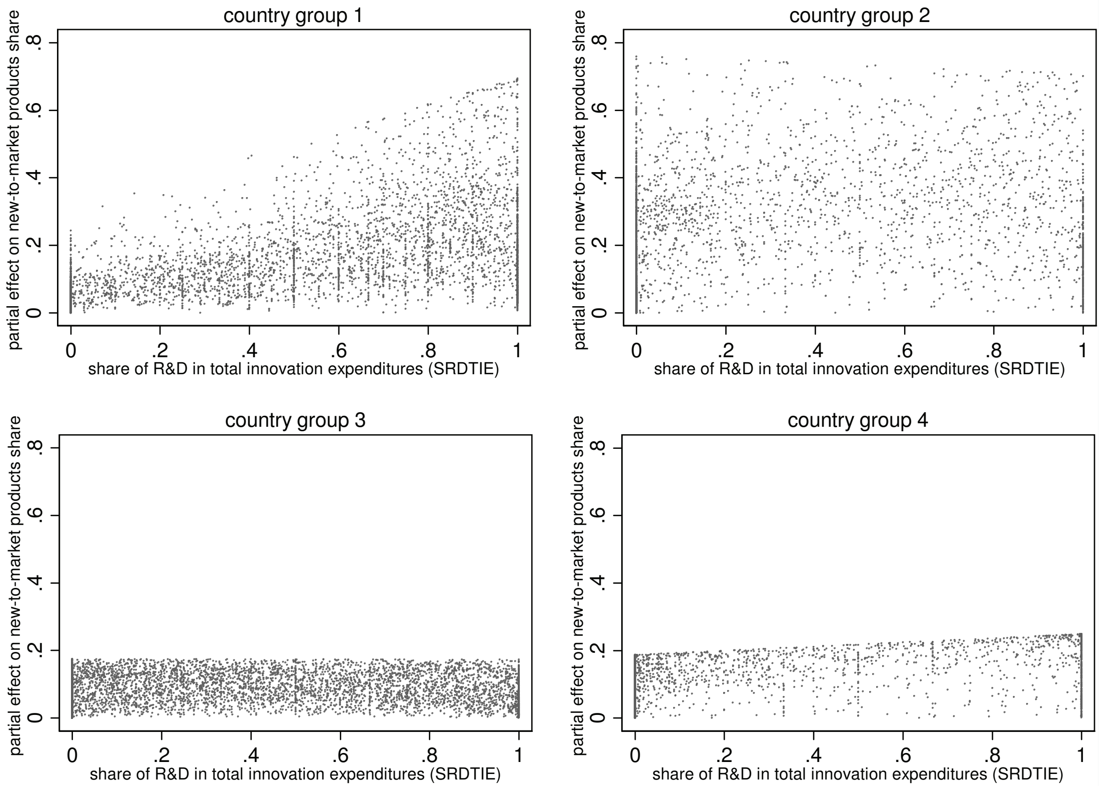

Figure 4: Partial effects of innovation intensity (INNOVI) on the share of new to market products in turnover for any given share of R&D in total innovation expenditures (SRDTIE) for each country group.

highest in country groups 1 and 2. For country group 1 the impact of the innovation intensity on the innovation output variable increases for higher shares of R&D in total innovation expenditures. In country groups 2 and 3 instead the data do not hint at any systematic relationship of this kind across firms. In country group 4 finally the relationship appears to be weakly positive, but at a considerably lower level than in country group 1. The evidence presented in Figure (3) indicates that strong R&D capabilities are most important in the countries with high technological capabilities to augment the impact of innovation investments on innovation output. Their impact is highest for pure R&D performers. These results can also be interpreted as showing that R&D does not generally increase the absorptive capacities of firms as in this case we should observe a positive relationship between the share of R&D in total innovation investments and the marginal effect of the innovation intensity on innovation output.

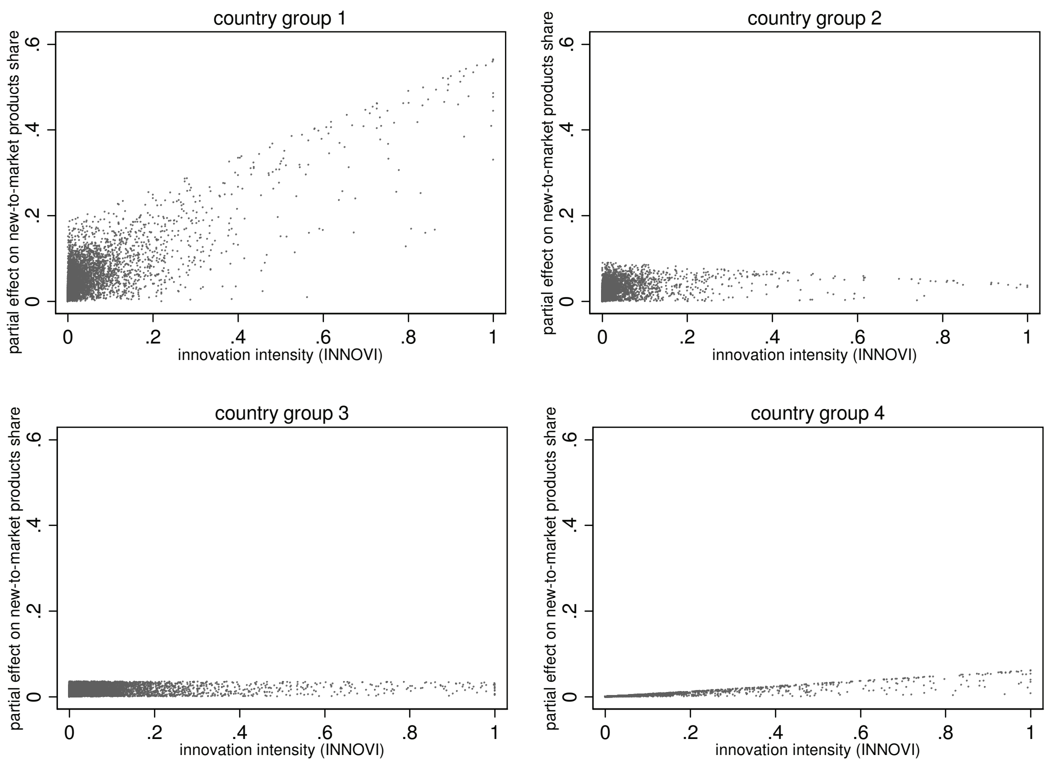

Figure 5: Partial effects of the share of R&D in total innovation expenditures (SRDTIE) on the share of new to market products in turnover for any given innovation intensity (INNOVI) for each country group.

Figure (5) presents the estimated marginal effects of the share of R&D in total innovation expenditures (SRDTIE) on the innovation output for the four country groups. They are largest for firms with higher innovation intensity in country group 1, particularly for firms with very high innovation intensities. No such relationship can be observed for country groups 2 and 3. A very weak positive relationship between the impact of R&D investments and the general innovation intensity of firms seems to exist also in country group 4. However, again the measured impact is at a tenth of the level observed for country group 1. For firms in the countries with the highest technological capabilities it pays on average to increase the the share of R&D in total innovation expenditures as the impact of the innovation investment on the innovation output increases as well. Hence, firms in these countries have an incentive to specialise in technologically more sophisticated innovations if these generate also higher returns to the firm. This evidence supports Hypothesis III.

Table 5 presents the estimation results for equations (20) and (21) with which we explore whether the impact of the use of different types of internal and external knowledge sources on innovation output is systematically higher in the technologically most advanced countries (Hypothesis IV). The left panel shows the marginal effects on innovation output for the variables summarising the importance of firm internal (SI) and firm external knowledge sources (SM and SPR) for the innovation process of the firm. The right panel instead shows the results for the model using the BASICNESS indicator.

Table 5 about here.

The impact of changes in the importance of the internal knowledge sources (SI) is highest for firms in country groups 1 and 3, and lowest for country group 4. As this variable is an indicator of firm specific capabilities this result indicates that the capabilities of the workforce as well as managerial capabilities to organise, coordinate and manage the innovation process are important determinants of innovation for firms in these two country groups.

The marginal effect of a change in the importance of market related knowledge sources for innovation shows no systematic pattern across country groups. The effect is highest for firms in country group 4 and country group 1. The size of the effects for this indicator are higher in each country group and in the pooled sample than those calculated for the indicator on internal knowledge sources. This underscores that it is generally very important for firms to observe or interact with competitors, suppliers and customers to successfully develop and launch innovations in order to position own products in the market and to learn from them in order to improve own products. Firms in the economically and technologically least developed countries in the sample seem to benefit most from this information source.

In contrast to the these findings variables SPR and BASICNESS summarising the importance of public research institutions for the innovation process of the firm show no impact on the innovation output. Only variable SPR it is weakly significant and negative with a very low marginal effect for the pooled sample. These outcomes have to be considered carefully, as our indicators are not able to capture the high variation in the quality of the interactions between firms and public research institutions. Firms can rely on public research institutions for the execution of simple test series for products or an expert opinion, or cooperate with them in cutting edge scientific research projects. The CIS does not provide adequate indicators to infer the true nature of this interaction. Better indicators are therefore needed to explore this link more thoroughly.

This final set of results does support Hypothesis IV only in part. Only firm internal knowledge sources have a higher impact on innovation output in the technologically and economically most advanced countries. Firm specific capabilities related to the innovation process become more important for firms in these countries as compared to firms in other countries.

5 Conclusions

The empirical results of this paper show that changes in the innovation intensity have on average a higher impact on the innovation output of firms the higher the average level of technological capabilities in the business sector of the countries in which these firms are located. R&D activities measured by the share of R&D in total innovation expenditures have a significant impact on innovation output only for firms operating in countries with the highest levels of technological capabilities in our sample, i.e. country groups 1 and 2.

The average level of technological capabilities in the business sector of a country matters with regard to the principal determinants of innovation output. Innovation investments and R&D outlays in these countries have a higher impact on the capability of firms to generate and introduce innovations in the market and reap the related economic opportunities across countries whether they imply the development of new technologies and products (country group 1) or the exploitation of catching up potentials (country group 2). Firms in countries with lower technological capabilities on the other hand may on average invest more into innovation activities but they get out less in terms of the effects of these investments on the innovation output as the data and the results for country group 3 show. The fact that firms in these countries don't reallocate their funds to investment opportunities that have a higher impact on the generation of new products and services hint at inertia induced by established technological capabilities and specialisation effects which work against a structural adjustment towards field of activity with higher a innovation potential.

Our results also indicate that R&D does not generally increase the absorptive capacities of firms. We observe a positive relationship between the share of R&D in total innovation investments and the marginal effect of the innovation intensity on innovation output only in the country group with the highest technological capabilities (country group 1). For firms in these countries it pays also to increase the share of R&D in total innovation expenditures as the impact of the innovation investment on the innovation output increases as well. Hence, they have an incentive to gear up R&D investments which induces a specialisation in technologically more sophisticated products.

Our findings also show that capabilities of the workforce as well as managerial capabilities to organise, coordinate and manage the innovation process are increasingly rated as being important across country groups the higher their average level of economic development as measured by real GDP per capita. This is reflected in the higher impact changes in the importance attached by firms to internal knowledge sources have on innovation output. As this indicator is an (imperfect) proxy for the quality of human capital accessible to firms this evidence supports findings that attach high importance to the education and the composition of human capital for aggregate growth processes in the proximity of the technological frontier (cf. Krueger and Kumar 2004, Aghion et al, 2006, Kneller and Stevens 2006). Especially for firms in country group 3 this evidence indicates that they try to exploit the more limited opportunities offered by the technological base in their fields of activity through higher quality products and services. This explains also the higher levels of innovation investment undertaken on average in these countries despite their lower impact on innovation output.

Finally, despite the fact that the CIS survey data may not be the most adequate data source to analyse the importance and impact of public research institutions on firms' innovation activities our results qualify statements that cooperations with public research institutions have an important effect for both catching up as well as cutting edge innovation and growth processes (see e.g. Mazzoleni and Nelson 2007, Aghion and Howitt 2006). They suggest that frontier research has a direct impact on only few industries and technology intense firms. For the average firms this direct linkage is of minor importance. The indirect linkage through the quality of human capital these institutions supply to firms seems to be more relevant in as it supports the development of firm internal capabilities.

The main conclusion of this paper is that firms specialising in the lower end of the quality spectrum requiring lower levels of technological capabilities do not have incentives to engage into R&D as long as their comparative advantage determined by lower cost and technological imitation and adaptation persists. Low productivity R&D activities tend to decrease the value of innovations and are unlikely to increase innovation success. Access to or command over technologies and practices used in technologically advanced high income countries are more important for firms in these countries. Scientific and technical training to apply and develop these further become more important as the lines between sophisticated imitation and the development of new products become indistinct. Strong R&D capabilities in firms are then essential in the economically and technologically most advanced countries. However, this is not a linear process of development and depends strongly on the established technological capabilities in the business sector of a country that cause inertia and get in the way of structural change towards fields of activity with higher returns to innovation investments. This may explain diverging patterns in the innovation dynamics observed in the EU (cf. Jungmittag 2006).

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Tables in the text

Table 1: Descriptive statistics

		Pooled Sample	Country Groups			
			1	2	3	4
New-to-market product share	Obs	70924	9630	12176	24586	24532
(s_m)	Mean	0.0417751	0.0463195	0.0318298	0.0509217	0.0357606
	Std. Dev.	0.1395286	0.1299935	0.1218605	0.1509116	0.1388557
	Min	0	0	0	0	0
	Max	1	1	1	1	1
Share of R&D in total innovation expenditure (SRDTIE)	Obs	70491	9606	12061	24585	24239
	Mean	0.1078222	0.2605741	0.0998909	0.1231771	0.0356586
	Std. Dev.	0.2693012	0.3720943	0.2575146	0.2826106	0.1652833
	Min	0	0	0	0	0
	Max	1	1	1	1	1
Innovation intensity	Obs	70923	9629	12176	24586	24532
(INNOVI)	Mean	0.0195831	0.0328667	0.0151891	0.0221301	0.0139974
	Std. Dev.	0.0789964	0.1060456	0.0635272	0.075272	0.0763558
	Min	0	0	0	0	0
	Max	4.10257	4.10257	1.341475	1	2.60843
Employment intensity	Obs	70824	9606	12162	24541	24515
(EMPI)	Mean	0.0892557	0.0161461	0.061719	0.027002	0.1938839
	Std. Dev.	0.2943797	0.1849283	0.2273818	0.2534759	0.3601414
	Min	0.0001042	0.000112	0.0001154	0.000106	0.0001042
	Max	10	9.90099	8.666667	10	8.952552
Investment intensity	Obs	69864	9385	11738	24339	24402
(INVI)	Mean	0.0945165	0.0916719	0.0926081	0.0679411	0.1230354
	Std. Dev.	0.3091024	0.3044447	0.2955496	0.2223311	0.3808782
	Min	0	0	0	0	0
	Max	9.990183	8.77193	8.204545	9.990183	9.940247
Start-ups	Obs	70924	9630	12176	24586	24532
($d_{startup}$)	Mean	0.0880943	0.0549325	0.067592	0.0499878	0.1494782
	Std. Dev.	0.283434	0.2278603	0.2510547	0.2179242	0.3565665
	Min	0	0	0	0	0
	Max	1	1	1	1	1
Log turnover	Obs	70924	9630	12176	24586	24532
(TURN)	Mean	14.52638	15.9828	14.55691	15.31501	13.14913
	Std. Dev.	2.098461	1.912389	1.804154	1.768628	1.786613
	Min	4.158883	7.076654	6.907755	6.907755	4.158883
	Max	24.71184	24.71184	22.22711	24.22431	21.56725
Export intensity	Obs	67606	8874	11185	24181	23366
(EXPI)	Mean	0.1847809	0.2243184	0.2925746	0.1343072	0.1704
	Std. Dev.	0.3002576	0.3003803	0.3524323	0.246133	0.3089388
	Min	0	0	0	0	0
	Max	1	1	1	1	1
Sources: Internal	Obs	70924	9630	12176	24586	24532
(SI)	Mean	0.7068411	1.262617	0.690046	0.8784674	0.3250041
	Std. Dev.	1.151182	1.325154	1.161399	1.216236	0.8327541
	Min	0	0	0	0	0
	Max	3	3	3	3	3
Sources: Market	Obs	70924	9630	12176	24586	24532
(SM)	Mean	0.7191078	1.25919	0.7403909	0.8308794	0.3845182
	Std. Dev.	1.159964	1.312405	1.202338	1.191025	0.9141503
	Min	0	0	0	0	0
	Max	3	3	3	3	3
Sources: Public research	Obs	70924	9630	12176	24586	24532
(SPR)	Mean	0.2385511	0.5026999	0.2362845	0.2429431	0.1315832
	Std. Dev.	0.6606715	0.8615577	0.646533	0.6735027	0.5192966
	Min	0	0	0	0	0
	Max	3	3	3	3	3
Basicness of R&D	Obs	70924	9630	12176	24586	24532
(BASICNESS)	Mean	0.0712312	0.184216	0.0744087	0.0740259	0.0225012
	Std. Dev.	0.2572124	0.3876804	0.2624456	0.2618183	0.1483099
	Min	0	0	0	0	0
	Max	1	1	1	1	1

Source: CIS 3 data (1998-2000) accessed at the Eurostat Safe Centre, Luxemburg. Country Groups: 1 - BE, DE, DK, FI, IS, LU, SE; 2 - CZ, EE, HU, SI, SK; 3 - ES, GR, IT, PT; 4 - BG, LT, LV, RO.

Table 2: Correlation between independent variables: Pooled sample

Pooled sample	SRDTIE	INNOVI	EMPI	INVI	$d_{start-up}$	TURN	EXPI	SI	SM	SPR	BASICNESS
SRDTIE	1										
INNOVI	0.278	1									
EMPI	-0.0082	0.0826	1								
INVI	-0.0236	0.0033	0.0505	1							
$d_{start-up}$	-0.0594	-0.0015	0.008	0.0481	1						
TURN	0.2992	-0.0105	-0.0545	-0.0792	-0.2054	1					
EXPI	0.1387	0.0031	0.0013	0.0024	-0.0398	0.1678	1				
SI	0.5695	0.0179	-0.0101	0.001	-0.0762	0.3671	0.1255	1			
SM	0.5249	0.0147	-0.0097	0.0072	-0.0749	0.3258	0.1208	0.8056	1		
SPR	0.4686	0.0186	-0.0057	0.0117	-0.0445	0.266	0.1055	0.5112	0.5187	1	
BASICNESS	0.5426	0.022	-0.0049	-0.0072	-0.0464	0.2845	0.1433	0.432	0.4057	0.6288	1

Source: CIS 3 data (1998-2000) accessed at the Eurostat Safe Centre, Luxemburg

Table 3: Fractional logit regression of the innovation production function

	Pooled sample		Country Groups							
			1		2		3		4	
Share R&D in TIE	0.0158	***	0.0310	***	0.0088	**	0.0057		-0.0007	
(SRDTIE)	(0.000)		(0.000)		(0.029)		(0.116)		(0.832)	
Innovation intensity	0.0524	***	0.0849	***	0.0638	***	0.0266	*	0.0251	***
(INNOVI)	(0.000)		(0.000)		(0.000)		(0.086)		(0.001)	
Employment intensity	-0.0115	*	-1.4870	***	-0.1410	***	-0.0082	*	-0.0056	***
(EMPI)	(0.069)		(0.001)		(0.002)		(0.075)		(0.002)	
Investment Intensity	0.0082		0.0151	**	-0.0105	*	0.0077		-0.0047	
(INVI)	(0.209)		(0.020)		(0.076)		(0.480)		(0.112)	
Start-ups	0.0153	***	0.0244	**	-0.0018		0.0126	*	0.0024	
($d_{startups}$)	(0.006)		(0.016)		(0.748)		(0.071)		(0.588)	
Log turnover	-0.0052	***	-0.0068	***	-0.0016	***	-0.0072	***	-0.0047	***
(TURN)	(0.000)		(0.000)		(0.068)		(0.000)		(0.000)	
Export intensity	0.0136	***	0.0164		0.0046		0.0141	*	0.0011	
(EXPI)	(0.009)		(0.149)		(0.259)		(0.070)		(0.756)	
Country dummies	YES		YES		YES		YES		YES	
Sector dummies	YES		YES		YES		YES		YES	
Heckman correction	YES		YES		YES		YES		YES	
Observations	66,946		8,837		10,910		23,993		23,169	
Pseudo R^2	0.2850		0.2295		0.3428		0.3268		0.4265	
Log-likelihood	-51413		-18387		-3033		-25002		-3478	
Rho	-0.1235		-0.0759		-0.1515		-0.1351		-0.2005	
p(rho)	0.000		0.000		0.000		0.000		0.000	

GLM Average marginal effects with SE in parentheses; Source: CIS 3 data (1998-2000) accessed at the Eurostat Safe Centre, Luxemburg. Country Groups: 1 - BE, DE, DK, FI, IS, LU, SE; 2 - CZ, EE, HU, SI, SK; 3 - ES, GR, IT, PT; 4 - BG, LT, LV, RO. Observations weighted with sample weights; Significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 4: t-test for difference in marginal effect across country groups for share of R&D investment in total innovation expenditures and innovation intensity

SRDTIE					
		Country group (y)			
		1	2	3	4
Country group (x)	pooled sample	-0.1130	0.0186	0.0338	0.0477
		(0.000)	(0.000)	(0.000)	(0.000)
	1		0.1317	0.1469	0.1608
			(0.000)	(0.000)	(0.000)
	2			0.0152	0.0291
				(0.000)	(0.000)
	3				0.0139
					(0.000)
INNOVI					
		Country group (y)			
		1	2	3	4
Country group (x)	pooled sample	-0.0062	-0.0140	0.0090	0.0124
		(0.000)	(0.000)	(0.000)	(0.000)
	1		-0.0079	0.0151	0.0185
			(0.000)	(0.000)	(0.000)
	2			0.0230	0.0264
				(0.000)	(0.000)
	3			.	0.0034
				.	(0.000)

diff = mean(x) - mean(y); Ho: diff = 0, Ha: diff != 0.

Table 5: Fractional logit regression of the innovation production function: the effect of innovation sources

	Pooled sample	Country Groups				Pooled sample	Country Groups			
		1	2	3	4		1	2	3	4
Share R&D in TIE	0,0155 ***	0,0278 ***	0,0068 *	0,0066 *	0,0021	0,0168 ***	0,0308 ***	0,0093 **	0,0068 *	-0,0015
(SRDTIE)	(0,000)	(0,000)	(0,077)	(0,066)	(0,514)	(0,000)	(0,000)	(0,031)	(0,066)	(0,680)
Innovation intensity	0,0505 ***	0,0844 ***	0,0641 ***	0,0248	0,0174 **	0,0542 ***	0,0845 ***	0,0640 ***	0,0287 *	0,0244 ***
(INNOVI)	(0,001)	(0,000)	(0,000)	(0,106)	(0,012)	(0,000)	(0,000)	(0,000)	(0,068)	(0,001)
Employment intensity	-0,0103 **	-1,4050 ***	-0,1310 ***	-0,0073 **	-0,0055 ***	-0,0112 *	-1,4920 ***	-0,1410 ***	-0,0079 *	-0,0056 ***
(EMPI)	(0,035)	(0,002)	(0,003)	(0,048)	(0,000)	(0,064)	(0,001)	(0,002)	(0,078)	(0,002)
Investment intensity	0,0066	0,0154 **	-0,0133 *	0,0041	-0,0049 *	0,0081	0,0151 **	-0,0105 *	0,0075	-0,0047
(INVI)	(0,304)	(0,020)	(0,100)	(0,727)	(0,090)	(0,215)	(0,020)	(0,075)	(0,497)	(0,115)
Start-ups	0,0154 ***	0,0228 **	-0,0007	0,0137 *	0,0022	0,0155 ***	0,0243 **	-0,0018	0,0128 *	0,0023
($d_{startups}$)	(0,005)	(0,019)	(0,909)	(0,054)	(0,632)	(0,005)	(0,017)	(0,747)	(0,065)	(0,602)
Log turnover	-0,0052 ***	-0,0066 ***	-0,0020 **	-0,0073 ***	-0,0050 ***	-0,0050 ***	-0,0069 ***	-0,0016 *	-0,0070 ***	-0,0048 ***
(TURN)	(0,000)	(0,000)	(0,028)	(0,000)	(0,000)	(0,000)	(0,000)	(0,084)	(0,000)	(0,000)
Export intensity	0,0120 **	0,0133	0,0029	0,0140 *	0,0008	0,0138 ***	0,0164	0,0047	0,0145 *	0,0012
(EXPI)	(0,019)	(0,216)	(0,476)	(0,074)	(0,818)	(0,008)	(0,151)	(0,258)	(0,062)	(0,739)
Sources: Internal	0,0080 ***	0,0082 ***	0,0052 ***	0,0067 ***	0,0029 **					
(SI)	(0,000)	(0,007)	(0,001)	(0,006)	(0,035)					
Sources: Market	0,0104 ***	0,0101 ***	0,0058 ***	0,0089 ***	0,0165 ***					
(SM)	(0,000)	(0,005)	(0,006)	(0,000)	(0,000)					
Sources: Public research	-0,0022 *	-0,0018	0,0002	-0,0022	-0,0016					
(SPR)	(0,095)	(0,458)	(0,911)	(0,128)	(0,178)					
Basicness of R&D						-0,0038	0,0009	-0,0017	-0,0049	0,0027
(BASICNESS)						(0,232)	(0,888)	(0,625)	(0,137)	(0,431)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Heckman correction	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	66.946	8.837	10.910	23.993	23.169	66.946	8.837	10.910	23.993	23.169
Pseudo R^2	0,2981	0,2404	0,3536	0,3358	0,4509	0,2852	0,2295	0,3429	0,3269	0,4265
Log-likelihood	-50476	-18127	-2983	-24666	-3329	-51402	-18387	-3033	-24997	-3477
Rho	-0,0123	-0,0152	-0,0296	-0,0264	0,0030	-0,1161	-0,0566	-0,1247	-0,1327	-0,1833
p(rho)	0,001	0,153	0,002	0,000	0,650	0,000	0,000	0,000	0,000	0,000

GLM Average marginal effects with SE in parentheses; Source: CIS 3 data (1998-2000) accessed at the Eurostat Safe Centre, Luxemburg. Country Groups: 1 - BE, DE, DK, FI, IS, LU, SE; 2 - CZ, EE, HU, SI, SK; 3 - ES, GR, IT, PT; 4 - BG, LT, LV, RO. Observations weighted with sample weights. Significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Appendix: Material not for publication

A Construction of country groups: data for cluster analysis

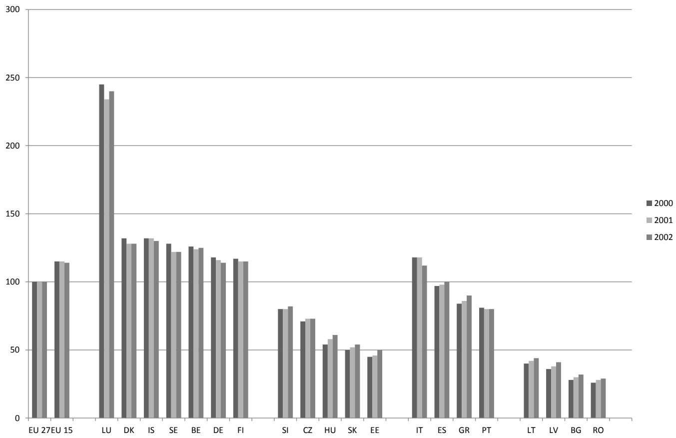

Figure 6: Real GDP per capita at PPP relative to the EU 27 average.

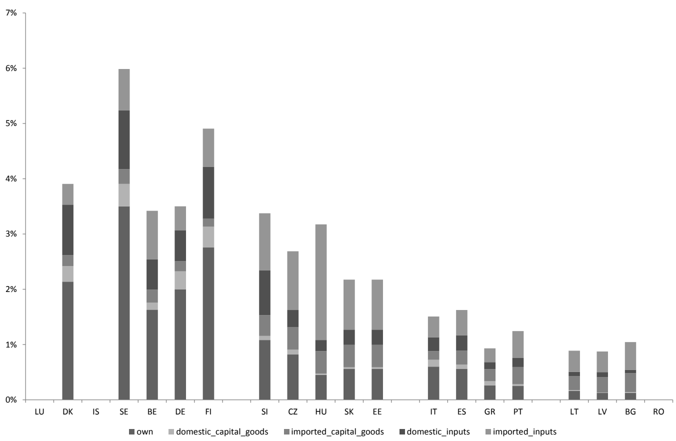

Figure 7: Direct and indirect R&D intensities from an input-output analysis used to construct the country groups taken from Knell (2008).

B Innovation production function for the econometric model

The principal dependent variable in this analysis - the share of sales due to new to market products - is directly related to the physical output of the firm. As a consequence we can take a standard production function for modelling the output of innovations at some point in time t augmented through the capital stock of knowledge capital as specified in equation 1 in the model as the starting point for our analysis. We write

$$Y_t^I = (\varsigma_1 L_t)^\alpha (\varsigma_2 C_t)^\alpha \left\{ [zK_{tot,t}]^\zeta [(1-z)K_{tot,t}]^{1-\zeta} \right\}^\gamma e_t^u. \tag{24}$$

Variable $\varsigma_1 L$ is labour needed to produce the measured revenue Y_t^I from innovations at time t, $\varsigma_2 C$ is ordinary tangible capital, $K_{tot,t}$ is the capital stock of total innovation investments, and e_t is the error. $K_{tot,t}$ is defined as: $K_{tot,t} = K_{m,t} + K_{n,t}$. $K_{m,t}$ is the measured capital stock of innovation investments into R&D, and $K_{n,t}$ is the measured capital stock of innovation investments for incremental innovation and technology transfer. The coefficient z_t is the share of the capital stock $K_{m,t}$ in $K_{tot,t}$, $z_t = K_{m,t}/K_{tot,t}$.

As the principal dependent variable is a share in total sales, we have to model the demand side as well. If the demand for innovations of the firm is specified as $Y_t^I = \overline{p}_t^{-\xi}$, where $\overline{p}$ is the average weighted price for innovations of type m and n, then equation (24) can be transformed into

$$S_{I,t} = (\varsigma_1 L_t)^{\alpha/\epsilon} (\varsigma_2 C_t)^{\beta/\epsilon} \left\{ [zK_{tot,t}]^\zeta [(1-z)K_{tot,t}]^{1-\zeta} \right\}^{\gamma/\epsilon} e_t^{u/\epsilon}, \tag{25}$$

where $\epsilon = \xi(\xi-1)^{-1}$ is the mark-up related to the elasticity of demand for new products launched by the firm. The data measure the share of sales of new to market innovations in total sales, hence we will divide equation (25) with $S_t = S_{I,t} + S_{N,t}$, where N is the number of products already on the market. Furthermore, consider that the current capital stock of innovation investments consists of the capital stock of period $t-1$ net of a fraction lost through depreciation, and current gross investment into innovation activities, such that $K_{tot,t} = K_{tot,t-1}^{\varphi-\upsilon} I_{tot,t-1}^{\upsilon}$. The same is true for the stock of tangible capital, $C_t = C_{t-1}^{\rho-\tau} Inv_{t-1}^{\tau}$. Taking these aspects into account as well as assuming that the capital and labour intensities of the production is equal across all product classes produced by the firm after some transformations we get

$$s_{I,t} = \left(\frac{L}{S}\right)_t^{\alpha/\epsilon} \left(\frac{C}{S}\right)_{t-1}^{(\rho-\tau)\beta/\epsilon} \left(\frac{Inv}{S}\right)_{t-1}^{\tau\beta/\epsilon} z_t^{\zeta\gamma/\epsilon}(1-z_t)^{(1-\zeta)\gamma/\epsilon} \left(\frac{K_{tot}}{S}\right)_{t-1}^{(\varphi-\upsilon)\gamma/\epsilon} \left(\frac{I_{tot}}{S}\right)_{t-1}^{\upsilon\gamma/\epsilon} S^{\omega} \left(\frac{e}{S}\right)_t^{u/\epsilon},$$

where $s_{I,t} = S_{I,t}/S_t$ is the share of new to market innovations in total sales and $\omega = (\alpha + \rho\beta + \varphi\gamma + u - \epsilon)/\epsilon$.

This equation cannot be estimated directly both for econometric and data related issues. Considering the econometric issues first the independent variables z_t and $(1 - z_t)$ should not be included in the same econometric model as they are perfectly collinear. Hence, in order to estimate this share equation we need to drop variable $(1 - z_t)$. The data related issues concern primarily the available data. The data we use are cross section data that have no information on both physical and intangible capital stocks. Given the cross sectional nature of the data it is also not possible to calculate the capital stocks following the method proposed by Hall and Mairesse (1995). We therefore have to drop variables C_{t-1} and $K_{tot,t-1}$ from the equation. Some of the effects of these stocks will be captured by the investment variables Inv_{t-1} and $I_{tot,t-1}$ as their elasticities are directly related to that of the stock variables, and because they represent gross investment, such that they include also replacements that for a constant depreciation rate capture also parts of the size effect of the stock variables.

The starting point for our econometric investigation is therefore the following share equation:

$$s_{I,t} = \left(\varsigma_1 \frac{L}{S}\right)_t^{\alpha/\epsilon} \left(\varsigma_2 \frac{Inv}{S}\right)_{t-1}^{\tau\beta} z_t^{\zeta\gamma/\epsilon} \left(\frac{I_{tot}}{S}\right)_{t-1}^{\upsilon\gamma/\epsilon} S^{\omega} \left(\frac{e}{S}\right)_t^{u/\epsilon}, \tag{26}$$

Using the variable names adopted in this paper gives then the share equation

$$s_{I,i} = (\varsigma_1 \text{EMPI})^{\alpha/\epsilon} (\varsigma_2 \text{INVI})^{\tau\beta} \, \text{SRDTIE}^{\zeta\gamma/\epsilon} \, (\text{INNOVI})^{\upsilon\gamma/\epsilon} \, \text{TURN}^{\omega} \, (\text{err})^{u/\epsilon}, \tag{27}$$

which underlies the estimated models in equations (18) through (21).