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Technological regimes and the variety of innovation behaviour

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ABSTRACT

This paper presents an integrated set of innovation taxonomies for firms and sectors. It discards the practice of representing industries by some average behaviour, instead characterising them by the distribution of diverse innovation modes at the firm level. The theoretical focus is on (i) Schumpeter's distinction between 'creative' and 'adaptive response', and (ii) differences regarding technological opportunities, appropriability conditions and the cumulativeness of knowledge. Applying statistical cluster analysis, the empirical identification is based on the micro-data of the Community Innovation Survey (CIS) for 22 European countries. The final cluster validation highlights the simultaneous diversity *and* contingency of firm behaviour with distinct technological regimes exhibiting systematic differences in the distribution of heterogenous firms.

Key Words: Technological regimes, innovation modes, sectoral taxonomy, industry classification, cluster analysis.

JEL Codes: D21, D28, O31, O33, O34.

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1. Introduction

Firm data on innovation and performance consistently show much heterogeneity of behaviour among individual companies. At the same time, sectoral data repeatedly demonstrate persistent and significant differences between sectors, e.g., with respect to average factor intensities, dominant corporate strategies, entry rates, or firm duration. For example, Malerba (2007) points at the apparent tension between these two stylised facts: while the first stresses variety, the latter emphasises common contingencies among firms operating within the same markets.

In the fields of industrial organization and business strategy the discussion about sectoral contingency vs. firm-level variety goes back to the contributions by Schmalensee (1985) or Rumelt (1991), and was further explored by McGahan and Porter (1997), Henderson and Mitchell (1997), or Kaniovski and Peneder (2002). In innovation research, it fares prominently in the literature on 'low- and medium-technology' (LMT) industries. For example, von Tunzelmann and Acha (2005, p. 429) argue that innovation plays an important role in every industry, observing "a varying degree of permeation of high technologies into low-tech and medium-tech as well as into high-tech sectors." Similarly, Kirner, Kinkel and Jaeger (2009) present ample empirical evidence that "high-, medium- and low-tech sectors themselves comprise a considerable mix of high-, medium- and low-tech firms" (ibid., p. 447).

However, in most empirical analyses the tension between the micro- and the meso-levels of observation largely remains unresolved. Persistent differences between sectors draw attention towards specific technology fields, where observed regularities in industry data are interpreted as if they represent the behaviour of the individual firms. Conversely, the variety of firm behaviour causes many researchers to focus exclusively on micro-data, frequently discarding any aggregate levels of analysis. The common observation of innovative firms in LMTs, or of a considerable number of non-innovating firms in high-tech sectors, is then viewed as an antagonism, which casts doubt on the usefulness of taxonomies that characterise the competitive or technological regime of an industry.

At a first glance, this debate may appear to be of purely academic interest, especially relevant to the methodology of classification. But the controversy also has profound practical implications for innovation policy. On the one hand, without a proper understanding of the co-evolution of variety and contingency government authorities are easily mislead into an obsession for 'high-tech' industries. A biased perception of innovation potentials can thus lead to the misallocation of public funds, if, for example, innovative companies in traditional sectors find it more difficult to access public funding than firms with lower innovation potential in a 'high-tech' industry. (Similar misperceptions, or hypes, can affect private capital markets, as demonstrated by the recent high-tech bubbles in the evaluation of corporate assets). On the other hand, industry characteristics matter and cannot be ignored. Their accurate understanding helps to design policy programs and tailor them more effectively to the needs of targeted firms. (Also in private capital markets the high specialisation of venture capital funds is a good example for the apparent benefits of industry expertise. It indicates the existence of important sectoral differences, which are not sufficiently accounted for by the mere assessment of the individual firm characteristics).

The research presented in this paper aims to help remove the impasse between the meso- and micro-led perspectives on innovation. It specifically contributes to the literature by creating a novel set of integrated taxonomies for both firms and industries, which explain sectoral characteristics by systematic differences in the distributions of heterogenous firms. In addition to providing novel classifications with an especially detailed and comprehensive empirical foundation, the final results convey a simple but important (and often ignored) message: Aggregate data, such as average R&D or patenting ratios, always reflect the variety of individual behaviours *and* their distribution in the population. Therefore they can never mean to represent the activities of the individual firm (except for uniform distributions). It also becomes evident that firm level variety is a natural element of, and not an antagonism to sectoral classifications. Innovative firms within LMT industries are as much part of their characteristic distribution as are non-innovating firms within high-tech sectors.

In creating the new classifications, the focus is on two specific themes of the Schumpeterian literature: (i) the distinction between *creative vs. adaptive* behaviour (Schumpeter, 1947), and (ii) the characterisation of opportunity conditions, appropriability conditions, and the cumulativeness of knowledge, together defining the so called *technological regime* under which a firm operates (Winter, 1984; Malerba and Orsenigo, 1993, 1997). The empirical identification is based upon CIS micro-data for 22 European countries made available at the Eurostat Safe Center, which offers an unprecedented comprehensive coverage of firm-level innovation activities.

In what follows, the research plan comprises three consecutive parts. In the first step, we characterise firms with respect to their individual innovation activities. In the second step, we apply statistical cluster methods to classify industries by the distribution of the firm types previously identified. In the final step, we validate the new taxonomies and take a closer look at the distribution of firm types within sector classes, revealing some marked and distinctive patterns in the interplay between firm level diversity and sector contingencies. The paper is organised accordingly. Section 2 explains the data, methodology, and rationales for the identification of innovation types. Section 3 discusses the statistical cluster analysis and presents the new taxonomies. Section 4 inspects the distribution of firm types within their sector groupings and highlights characteristic differences. Section 5 summarises and concludes.

2. The identification of innovation types

2.1 Methodology and data

It is exactly the variety of firm behaviour, which motivates the search for regularities and systematic empirical patterns through the creation of classifications. Substituting structural knowledge for exhaustive information concerning single attributes, taxonomies direct our attention towards characteristic dimensions, according to which relative similarities or differences can be identified.[1] Thus they allow us to take account of heterogeneity, while simultaneously forcing us to be selective.

Innovation research is a particular case in point, where the high diversity at the micro-level corresponds with a strong interest in taxonomic work.[2] The most famous example goes back to Pavitt (1984), who presented an empirical classification of 'sectoral technological trajectories', which classifies industries according to whether they can be characterised as being 'science based', 'production intensive', or 'supplier dominated', with the second group subdivided further into 'scale intensive production' or 'specialised suppliers'. This classification proved extremely influential and motivated numerous extensions and further refinements. Among them, the most important taxonomies are provided by Marsili (2001) and Castellacci (2008). Other notable examples are to be found in Evangelista (2000) or deJong and Marsili (2006). In contrast, Peneder (2001) focused on average factor intensities, where R&D is only one category besides the expenditures on labour, capital, and advertising.

Since the 1990s, the availability of firm data from national innovation surveys induced several papers which are very critical of the presumed sectoral regularities in innovation patterns. Rather than classifying industries or sectors, they focus on the distinct innovation types observed at the micro-level. Examples are Cesaratto and Mangano (1993), Arvanitis and Hollenstein (1998), Hollenstein (2003), Arundel and Hollanders (2004), or Leiponen and Drejer (2007). Curiously, so far neither the researchers working on sectoral classifications (including this author), nor those on firm level taxonomies of innovation went the step further to integrate both dimensions within a joint classification of firms *and* industries.

Another motivation for creating the new classifications is the availability of new and more comprehensive data. In particular, the new taxonomies benefit from access to the micro-data of the

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[1] See, e.g., Peneder, (2003).

[2] See, e.g., von Tunzelmann and Acha (2005).

Third Community Innovation Survey (CIS), which was made available by the Eurostat Safe Center. These data cover the innovation activities of more than 78,000 firms from 22 European countries over the period 1998 to 2000. For the purpose of this study, the major advantage of the CIS database is its very detailed account of variables on innovation behaviour. Another strength is the use of a stratified sample of companies. While the sampling rates differ across countries, the stratification by size-class and sector of activity should ensure that the samples are representative. Conversely, one major disadvantage of the CIS surveys is the lack of time-series, which means that researchers only have access to cross sectional information and are not allowed to analyse different waves of the survey within a joint data panel.

One must also be prepared to find a considerable amount of unsystematic 'noise' in the individual data. In order to increase the sample sizes per sector and render the results more robust, when identifying the sectoral classifications in the second stage, we aggregate the data by broad country groups. We distinguish between (i) *Continental Europe* (Austria, Belgium, Germany, and Luxembourg); (ii) *Northern Europe* (Denmark, Finland, Iceland, Norway and Sweden); (iii) *Southern Europe* (Greece, Italy, Spain and Portugal); (iv) *NMS10* (the Czech Republic, Estonia, Latvia, Lithuania, Hungary, the Slovak Republic, and Slovenia - i.e. the new EU member states from the first wave of eastern expansion); and finally (v) *NMS2* (Bulgaria and Romania, which represent the latest wave of accession countries). Table 1 summarises the sample sizes by country and country groups.

{Insert about here: Table 1. The firm sample by country and country groups}

For the purpose of empirical analyses industries and technologies are often treated interchangeably, with the notion of a 'regime' allowing a certain degree of flexibility. This paper also applies the notion of technological regimes to sectoral data. However, it makes a difference, whether the sectoral boundaries reflect technologies, products, or a hybrid of the two. Official classifications of sectors and industries usually reflect similarities in the products the firms supply rather than the technology they use. In many instances these largely coincide (e.g. the use of metal processing technologies in the manufacture of metal products). But in other instances, the distinction clearly matters. Von Tunzelmann and Acha (2005, p. 409) point at the example of biotechnology, which is used e.g. in the sectors of farming, food processing and the pharmaceutical industry. The knowledge environment (e.g. R&D intensity, patent use) and other characteristics (e.g., the importance of venture-capital) is often more similar among biotech-based firms in different industries than between these and non-biotech firms (let's say, producers of organic food), which happen to be classified within the same sector by current statistical conventions. To the degree that similar products based on different technologies are potential substitutes, one may therefore prefer to speak of 'competitive-' instead of 'technological regimes' when referring to industry classifications.

2.2 Creative vs. adaptive behaviour

For identifying firm innovation types, we first turn to the classic distinction between 'creative' and 'adaptive response'. It goes back to Schumpeter (1947, p. 150), who defines *creative response* as innovation, or doing "something that is outside of the range of existing practice". More specifically, he distinguishes five types of innovation: new products, new processes, new resources, new markets, and new forms of industrial organization (Schumpeter, 1911). In contrast to innovation, adaptive response is defined by the mere reaction to changes in the exogenously given business conditions.

Another point to emphasise is that for Schumpeter innovation is synonymous with *entrepreneurship* and thus strictly rooted in individual behaviour. Hence, the "frequency of its occurrence in a group, its intensity and success or failure" depends on "individual decisions, actions and patterns of behaviour. Accordingly, a study of creative response in business becomes coterminus with a study of entrepreneurship" (1947, p. 150). In contrast to Schumpeter's narrow focus on innovation, there exist other influential theories of entrepreneurship which explicitly account for 'adaptive' behaviour. The latter includes (i) imitation and technology adoption (Schultz, 1975), as well as (ii) the alertness to price differentials caused by market frictions (Kirzner, 1997).[3] Reflecting this variety of opportunities to make a profit, we distinguish the following innovation types among the firms sampled in the European Community Innovation Survey (CIS):

— *Creative* firms, as defined by Schumpeter, are characterised by own innovations. For the purpose of this study, we focus on technological change initiated by firms performing either *process innovations,* developed mainly by their own enterprise or enterprise group (CrPc), *product innovations* that are new to the market (CrPd), or *both* (CrPP).

— All other firms are characterised by *adaptive* behaviour. Among them we distinguish the group of *technology adopters* (AdTA), which is motivated by the entrepreneurship theory of Schultz (1975) and comprises firms that either record product innovations that are new to the firm, but not to the market; or process innovations mainly in co-operation with other enterprises or institutions.

— Third, there is a large residual group of firms with adaptive behaviour that pursue *opportunities other than from technological innovation* (AdOth). These may originate in pure market co-ordination (Kirzner) as well as from non-technological innovations (e.g. in terms of exploiting new resources, markets, or industrial organization in the sense of Schumpeter's general definition of innovation).

Finally, it should be noted, that the identification of classes which are mutually exclusive also requires a certain order of priorities among these rules. This implies, for example, that firms which simultaneously adopt external technologies and generate their own innovations are classified within the group of creative firms. Table 2 summarises the rules for identifying the firm-level types with the data available from the CIS surveys.

[3] See, e.g., Peneder (2009a).

2.3 Technological regimes

Our second focus is on 'technological regimes', a concept which also emenates from Schumpeterian economics, but adds detail by pointing at the intrinsic differences between technologies (Nelson and Winter, 1982; Winter, 1984; Malerba and Orsenigo, 1993). Consistent with its evolutionary foundations, the heterogeneity of firms is taken for granted. However, it is also assumed that firms operating within the same regime are likely to share some proximate organisational and behavioural features (Dosi and Malerba, 1996). This is where the tension between variety at the level of individual firms and shared constraints at the industry level begins to matter. Winter (1984, p. 293) explains technological regimes as follows:

> "there are differences in a variety of related aspects, including such matters as the intrinsic ease or difficulty of imitation, the number of distinguishable knowledge-bases relevant to a productive routine, the degree to which successes in basic research translate easily into successes in applied research (and vice versa), the size of the resource commitment typical of a 'project' and so forth. To characterise the key features of a particular knowledge environment in these various respects is to define a 'technological regime'."

Malerba and Orsenigo (1993) specify technological regimes in terms of *opportunity* conditions, *appropriability* conditions, and the *cumulativeness* of knowledge. Taken together, these define the knowledge and learning environment within which firms operate.

Opportunity

Beginning with 'opportunity conditions', Malerba and Orsenigo (1993, p. 48) explain that these "reflect the ease of innovating for any given amount of money invested in research." But how can we empirically identify opportunity conditions? One tempting choice would be measures of innovation success. One example of such a variable available in the Community Innovation Survey is the share of new products in a firm's total sales revenues. But opportunity is not the same as success. It refers to potential and not to actual realisation; this distinction is especially important under the conditions of fundamental uncertainty prevalent in innovation processes. Instead, "technological opportunities reflect the likelihood of innovating for any given amount of money invested in research" and thus "provide powerful incentives for the undertaking of innovative activities" (Malerba and Orsenigo, 1993, p. 48).

Opportunities cannot be explained solely by technology. They relate to profit and hence depend on the characteristics of demand. For instance, Sutton (1998) defines technological opportunities in the context of an equilibrium model of market concentration as "the extent to which a fragmented industry can be destabilized by the actions of a firm which outspends its many small rivals on R&D. ... Hence it reflects both the patterns of technology and tastes and the nature of price competition in the market" (Sutton, 1998, p. 70).[4]

We therefore indicate opportunities by providing data on the effort and resources invested in innovation activity. While these efforts may either succeed or fail, dependent on capabilities, exogenous shocks, or the accurateness of individual perceptions, they serve as the best proxies available, indicating the opportunities from technological innovation as perceived by the market participants. Using the CIS micro-data, we discriminate four firm types according to the nature of perceived technological opportunities:

— *None*, if the firm undertakes neither intramural R&D nor any purchase of external innovations;
— *Acquisitions* (ACQU), if the firm innovates only by means of purchasing external R&D, machinery, or rights (patents, trademarks, etc.);
— *Intramural R&D* (IR&D), if the firm undertakes its own R&D, but the ratio of innovation expenditures to total turnover is less than five per cent; and finally
— *High R&D* (HR&D), if the firm reports intramural R&D and a share of innovation expenditures in total turnover of more than 5 per cent.

[4] Sutton (1998) depicts this general opportunity condition as the 'alpha-coefficient' and the aforementioned ease of innovation (i.e. an elasticity relating R&D expenditures to product quality) as the 'beta-coefficient'.

{Insert about here: Table 2. Identifying assumptions for the firm innovation types}

Appropriability

Quoting Malerba and Orsenigo (1993, p. 48), appropriability conditions "summarise the possibilities of protecting innovations from imitation and of extracting profits." Firms have a number of formal and informal means at hand by which they can protect their innovations. But depending on the particular nature of the knowledge to be protected (i.e. its complexity, tacitness, etc.), the precise institutional arrangements (e.g. patent laws) or industrial organisation (such as the degree of vertical or horizontal integration), only few, if any, might be truly effective for an firm's specific innovation.

The CIS offers a comprehensive set of indicators in the questionnaire, among which we use the following rules of identification to separate firms according to their appropriability regime:

— *None* if firms apply neither of the tools for appropriation;

— *Strategic* (STRAT) if firms rely exclusively on either secrecy, complexity of design, or lead-time advantage to protect their innovations;

— *Formal means other* than patents (FORM), if firms use the registration of design patterns, trademarks, or copyright;

— *Patents* (PAT+) if these are applied (with or without either strategic or other formal means), and finally

— *Full arsenal* (FULL) if firms simultaneously use all the three methods of protection.[5]

[5] Again it is necessary to impose certain priorities among the identification rules, so that the firm types become mutually exclusive. For example, the use of patents overrules any other means, except the simultaneous use of all three categories. Similarly, other formal methods overrule strategic methods.

Cumulativeness

Our third characteristic of technological regimes regards the degree of cumulativeness of knowledge as experienced by the individual firm. The question therefore is, to what extent a firm's ability to create new knowledge depends on the stock of knowledge it has already acquired. Cumulativeness is high, if firms with a head start can more easily add to their existing stock of knowledge than technological laggards, and thus create first mover advantages. It therefore "denotes economic environments characterised by increasing returns" to knowledge creation (Malerba and Orsenigo, 1993, p.49).[6]

Given the abstract nature of the concept, the CIS does not provide any direct measure of cumulativeness. However, we pursue an indirect identification, combining two aspects which are covered by the CIS. First, we distinguish according to the relative importance of internal vs. external sources of information. Second, we apply opposite rules of identification depending on whether the firm appears to be a technological leader or follower.

— If a firm, that previously has been characterised as 'creative', reports that internal sources of knowledge are more or at least as important as external sources, we infer that it operates under a regime of *high cumulativeness*. For the firms belonging to the type of adaptive behviour, we reverse the rule. We consider their knowledge environment to be highly cumulative, if they report that internal sources of information for innovation are less important than external ones.

— Conversely, we identify *cumulativeness to be low*, if a 'creative' firm sources more information for its innovations from external than from internal sources, or if an 'adaptive' firm reports that internal sources are more or at least as important than external sources.

[6] Cumulativeness and appropriability conditions are related, but nevertheless different concepts. For instance, consider how appropriability conditions feature prominently in static welfare analysis (spillovers), whereas cumulativeness refers to dynamic properties of a system, such as path dependence and lock-in effects.

While these rules may seem rather complex at first sight, they follow from one straightforward consideration. If knowledge is highly cumulative, creative firms, whom we presume to be closer to the technological frontier, will more heavily rely on their own sources of information due to increasing returns of own knowledge generation. Conversely, adaptive firms, who presumably are more distant from the technological frontier, will have to acquire knowledge for their innovation activities from external sources. The reason is that their lower stock of accumulated knowledge reduces their chances to succeed by own R&D. However, when creative firms operate within a regime of low cumulativeness, the lack of increasing returns to own knowledge creation implies a stronger need to source external knowledge in order to stay at the technological frontier. At the same time, the internal creation of knowledge becomes a viable strategy for adaptive firms, whose aim is to catch-up and reduce the technology gap.

2.4 The variety of combinations

Apparently, the different dimensions of firm behaviour and technological regimes are interrelated. Since we classify them at the micro-level, we are able to observe characteristic peaks in the distribution as well as a striking variety of combinations of individual innovation types.

Table 3 provides detail on the pairwise co-identification of firms. The shared properties are consistent with *a priori* expectations. The crosstabulation also demonstrates that each taxonomy represents an independent analytical dimension as supposed by the received theory on technological regimes. Neither classification is redundant in the sense that it could be replaced by one of the others. In every instance except one, we see that firms belonging to the same class of a certain taxonomy are distributed among different classes in the other. The only exception is the largely overlapping group of non-innovating firms, which is consistently comprised of an almost identical set of firms in each of the classifications.

To give some examples for the diverse and yet characteristically pointed distribution of firm types, about sixty per cent and more of the creative firms doing product innovations are classified as either intramural or even high R&D performers. While R&D thus proves to be the dominant driver of product innovations, about a quarter of the firms pursue them mainly by the acquisition of external knowledge. Among the creative firms doing process innovations, the majority depends only on the external acquisition of new knowledge, but an almost equal share of firms is doing their own R&D. About 40 per cent of the firms classified as pure technology adopters also perform some own R&D, which is consistent with the concept of absorptive capacity (Cohen and Levinthal, 1989, 1990).

Similarly, the share of firms using patents is highest among creative firms, followed by technology adopters and finally the firms pursuing opportunities other than from technological innovation. However, the data also show a great diversity in the use of appropriation mechanisms. For example, among the group of high R&D performers, 40 per cent use patents (half of them applying the full arsenal of instruments), but about 18 per cent apply only strategic means, such as secrecy or lead time. The covariation is more pointed for cumulativeness and appropriability, where the vast majority of firms applying the full arsenal of tools to protect their innovation is also characterised by a high cumulativeness of knowledge. The covariation with cumulativeness is again positive but less pronounced for other firms applying patents and those only using strategic measures. Finally, we find that more than two thirds of creative firms are characterised by high cumulativeness, whereas 60 per cent of pure technology adopters operate within a regime of low cumulativeness. Again, we have observed much diversity among individual firms together with characteristic patterns in the overall distribution.

{Insert about here: Table 3. Crosstabulation of firm types (shares in %) }

Finally, Table 4 compares the share of firm types with respect to the five broad country groups. In addition to the heterogeneity between countries, the table displays a consistent congruence in the relative importance of firm types that relate 'more innovativeness' with higher levels of economic development (e.g., GDP per capita). For example, we find considerably higher shares of creative firms in the Continental and Northern European countries than in the NMS10 and NMS2. The same applies to the shares of high R&D performers and firms using the full arsenal of appropriation methods. In contrast, the share of firms, to which neither internal nor external sources of information for innovation are important, is highest in the NMS2, followed by NMS10, the South, North and Continental Europe.

{Insert about here: Table 4. Distribution of firm types by country group in %}

3. The statistical cluster analysis

For the identification of the sectoral taxonomies, we apply statistical cluster analysis, which is defined as "the art of finding groups in data" such that the degree of natural association is high among members within the same class and low between members of different categories (Kaufmann and Rousseuw, 1990). The clustering procedure starts with a given data matrix of $i = 1, ..., n$ observations for which characteristic attributes x are reported for $j = 1, ..., p$ variables. The discriminatory variables are the standardised shares of the various firm types in the overall firm population of a sector. The shares are aggregated by four broad country groups (Continental and North, South, NMS10, and NMS2). Each sector per region is treated as an independent observation, thereby creating independent taxonomies for each country group in addition to the synthesis of a common 'consensus' classification (Gordon, 1999).

The initial data set of the dimension n x p is transformed into a symmetric (dis)similarity matrix of dimensions n x n observations with d_{ih} being the coefficients of (dis)similarity for observations x_i and x_h.

(1)
$$D_{n,n} = \begin{bmatrix} 0 & \cdots & & & 0 \\ d_{21} & 0 & \cdots & & \\ d_{31} & d_{32} & 0 & \cdots & \vdots \\ \vdots & & \vdots & & \\ & \cdots & d_{ih} & \cdots & \\ & & \vdots & & \\ d_{n1} & d_{n2} & \cdots & d_{n(n-1)} & 0 \end{bmatrix}$$

For any observations x_i , x_h and x_g with i, h, and g = 1, ..., n, located within measurement space **E**, the desired formal properties of the (dis)similarity matrix $\mathbf{D}_{nn}$ are defined as follows (Anderberg, 1973):

1. $d_{ih} = 0$ if and only if $x_i = x_h$, i.e. for all observations the distance from itself is zero and any two observations with zero distance are identical;

2. $d_{ih} >= 0$, i.e. all distances are non-negative;

3. $d_{ih} = d_{hi}$, i.e. all distances are symmetric; and finally

4. $d_{ih} <= d_{ig} + d_{hg}$, known as the triangle inequality, which states that going directly from x_i to x_h is shorter than making a detour over object x_g.

The combination of the first and second properties assures that $\mathbf{D}_{nn}$ is fully specified by its values in the lower triangle. The fourth property establishes that **E** is an Euclidean space and that we can correctly interpret distances by applying elementary geometry. Any dissimilarity function that fulfils the above four conditions is said to be a *metric*.

The cluster analysis is proceeded by a two-step approach which combines *k*-means and agglomerative hierarchical methods. The *k*-means method produces a first partition, which reduces the large initial data sets, so they can be used more effectively in the second step of hierarchical clustering.[7] The *k*-means method also has the advantage that the initial case assignments remain reversible during the course of iterations. In this first step, we use the *Euclidean distance* e_{ih}, which is a direct application of the Pythagorean Theorem and has the advantage of separating outliers particularly well:

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[7] For determining the initial number of partitions *k*, we consistently apply the following self-binding rule-of-thumb: “Choose the lowest number *k* that maximizes the quantity of individual clusters *l* which include more than 5% of the observed cases“.

(2) $$euc_{ih} = \sqrt{\sum_{j=1}^{p}(x_{ij} - x_{hj})^2} \qquad 0 \le euc_{ih} < \infty$$

For the purpose of further refinement, the resulting cluster centers are redefined as objects for the subsequent agglomeration method, which provides a more detailed hierarchical representation. For this final identification, we use the Angular Separation measure ang_{ih}, which has the particular advantage of focusing on differences in the shape of the sector profiles, while remaining sensitive to size displacements:

(3) $$ang_{ih} = \frac{\sum_{j=1}^{p} x_{ij} x_{hj}}{\sqrt{\sum_{j=1}^{p} x_{ij}^2 \sum_{j=1}^{p} x_{hj}^2}} \qquad -1{,}0 \le ang_{ih} \le 1{,}0$$

The cluster dendrograms in Figure 1 illustrate the outcome of the hierarchical clustering. The branches on the bottom of the charts represent the clusters which resulted from the first *k*-means algorithm, while the root on top represents the entire set of objects. As we move upwards on the chart, the degree of association between objects is higher, the sooner they are connected by a common root. Conversely, objects or groups are the more dissimilar, the longer they remain disconnected.

{Insert about here: Figure 1. Dendrograms for Average Linkage Method and Angular Separation Measure of Similarity }

The resulting sectoral taxonomies for each country group are documented in Table A.1 to A.4 in the Annex. They demonstrate a certain degree of heterogeneity among the country groups and are therefore the more accurate tools, e.g. when applied to datasets specific to these countries. For identifying the joint consensus classification, we choose the most frequent characterisation of a sector. Only in cases when two different types occur with the same frequency, do we give priority to the characterisation as identified for the country group ‘Continental/North’. Table 5 summarises the final consensus classifications for each of the four resulting taxonomies.

{Insert about here: Table 5. The sectoral taxonomies}

Finally, Table 5 presents another sectoral classification (InnoType) which aims to summarise the ‘relative innovation intensity’ inherent in the characterisation of the other taxonomies. It is important to understand that this final taxonomy is by no means a culmination of the others. On the contrary, it is a simplification that can be useful for some applied analyses, by drawing attention to the general innovativeness of sectors without necessarily invoking the abstract and relatively theory-loaded interpretation of the four original sector classifications.

Even though the respective labels depict only the characteristic most pronounced in the firm distribution, the previous discussion should have made clear that one must always acknowledge the heterogeneity within each sector group. To summarise, this final taxonomy comprises the following types:

— *High innovation intensity:* Sectors are characterised by a high share of creative firms focused on product innovations (either alone or in combination with process innovations) and many firms performing high intramural R&D. Typically, the appropriability regime depends on the use of patents (frequently applied together with other measures) and knowledge is highly cumulative. This group is mainly comprised of ICT-related sectors such as computers and office machinery, electrical equipment, communication technology, precision instruments, and computer related services. Other sectors within this group are machinery and R&D services.

— *Intermediate-to-high innovation intensity*: This group is comprised of sectors with an intermediate share of creative firms mostly involved in process innovations, and many firms performing R&D, albeit expenditures are less than 5 per cent of turnover. Cumulativeness of knowledge is high or intermediate and firms frequently use patents for appropriation. Examples are chemicals, motor vehicles, other transport equipment, or telecommunication and postal services. The latter is distinctly characterised by a high share of creative firms with product innovations in combination with a strong dependence on the external acquisition of new technology.

— *Intermediate innovation intensity*: This group is the most heterogeneous of classes, but all sectors share a large number of firms pursuing opportunities through the acquisition of external innovations. Accordingly, appropriability measures are relatively weak, with some importance ascribed to strategic means. In this group we find wood and wood products, pulp and paper, metal products, as well as air transport, financial intermediation and other business services.

— *Intermediate-to-low innovation intensity*: The main characteristic of this group is the high share of firms with adaptive behaviour, pursuing opportunities through the adoption of new technology. Accordingly, the prevalent mode of innovation is the acquisition of new technology. For most firms appropriability conditions are weak and the cumulativeness of knowledge is low. Examples are the food sector, publishing and reproduction, electricity and gas, or insurance and pension funding.

— *Low innovation intensity*: Finally, this relatively homogenous group is characterised by a predominance of firms pursuing opportunities other than from new technologies, typically performing no innovation activities nor applying any measures for appropriation. For the majority of firms the cumulativeness of knowledge is low or irrelevant, since no information regarding innovation is pursued. Examples are wearing apparel, leather products, recycling, as well as wholesale trade and land and water transport.

4. Variety *and* contingency: an integrated perspective

The new taxonomies stress the diverse *and* contingent nature of innovation behaviour, which depends on the capability to match a firm's organisation and strategy to the technological, social and economic restrictions imposed by its competitive environment. For that purpose, the boxplots in Figure 2 and Figure A.1 (in the Annex) help to validate the cluster outcomes in three ways. First, they demonstrate the discriminatory power of the different categories. Second, they allow us to assess the accurateness of their interpretation. Third, displaying the differences in the shape and dispersion of firm types between the various sector types, they provide us with an integrated view of variety and contingency in innovation behaviour.

The charts are easy to read. The box itself comprises the middle 50 per cent of observations. The line within the box is the median. The lower end of the box signifies the first quartile, while the upper end of the box corresponds to the third quartile. In addition, the lowest and the highest lines outside the box indicate the minimum and maximum values, respectively.

The charts in Figure A.1 (in the Annex) document the distribution of firm types within their own respective sector classifications. They illustrate how firm-type variety occurs together with systematic differences between sector-types. For instance, the first chart in Panel A reveals a distinctive descending order in the standardised value of the share of creative firms doing product innovation for the different categories of the Schumpeter innovation types (SpType). Consistently, we find an opposite ascending order with respect to the industry shares of non-innovating firms. In contrast, firms classified as pure process innovators or technology adopters are more evenly spread across the sector types.

A different pattern applies to opportunity conditions (Panel B), where the share of firms classified as high R&D performers is extremely concentrated among a few sectors that all fall within the cluster labelled HR&D. Conversely, we find very little variation in the share of high R&D performers among the three remaining sector types, which are labelled according to the respective peak in the share of one of the firm types.

For appropriability conditions (Panel C), the share of firms applying patents to protect their innovation peaks in one cluster of industries, and then decreases continuously. However, as observed before, there tends to be much variation of appropriability measures within each group. Only the share of firms using patents shows a satisfactory degree of discrimination between sectors, whereas the discriminatory power of the share of firms that apply other formal tools or use strategic means of appropriation is relatively modest.

Finally, with respect to cumulativeness (Panel D), the boxplots exhibit a pronounced descending order for the share of firms operating within a knowledge environment characterised by high cumulativeness, a moderate descending order for the share of firms subject to low cumulativeness of knowledge, and a strictly rising order for the share of firms reporting no sources of information for innovation.

The boxplots in Figure 2 provide a similar window, but spot the main features of the distribution of firms classified according to the four initial taxonomies across the categories formed in the final sectoral classification of innovation intensity (InnoType). For example, in Panel A we find an almost linear positive association between the degree of innovativeness in the sector and the share of creative firms carrying out product innovations. In contrast, the figures show consistent negative associations with respect to the share of firms pursuing opportunities other than from technological innovation. Overall, the types distinguishing between creative and adaptive innovation behaviour discriminate extremely well – and they do so not just at the respective end of the distribution, but also in the categories of intermediate innovation intensity. Judging on the overall discriminatory power of the classification, this taxonomy appears to be the most successful.

We find a similar quasi-linear relationship with respect to the cumulativeness of knowledge and the innovation intensity of sectors (Panel D). The share of firms classified as operating within a highly cumulative knowledge environment is largest among the sectors with a high innovation intensity, followed by those characterised as medium-to-high, intermediate, or medium-to-low, and smallest among the sectors with a low innovation intensity. The positive association between innovation intensity and the cumulativeness of knowledge is thus remarkably pronounced.

At this point, one may argue that the observed patterns of association are quite predictable and easily conceived. However, the next two panels demonstrate how deceptive it can be to take something for granted *ex post*, and how different the actual distributions can be for similarly expected positive relationships. One example is the extreme concentration of firms pursuing opportunities by means of high R&D expenditures among a few sectors that have been classified as highly innovative (Panel B). While the classification is very successful in the sense that separating this cluster captures almost the entire variation between groups, it has no power to discriminate between any of the remaining sectors of intermediate to low innovation intensity. This raises concerns about the usefulness of taxonomies that separate industries only on the basis of their R&D intensity. They capture well the high-end of the distribution, but miss much of the intermediate forms that shape the innovation activities in the low and medium technology sectors (LMTs). In contrast, our classification complements R&D expenditures by additional variables, such as the share of firms pursuing opportunities through the acquisition of new technology, which peaks in the sectors of intermediate and intermediate-to-low innovativeness.

Turning to the share of firms applying patents (Panel C), we find another distinct pattern of a positive association with the sectors' innovation intensity. What makes the difference is a marked covariation of the variance and the mean in this variable. This produces a concave distribution, where the positive association is much stronger in the fourth and third quartiles than in the second and first, and where we find some industries with no firms in our sample using patents in every sector group. It follows that the actual use of patents is a valid indicator of a sector's innovativeness, and is so at an increasing rate. But the reverse inference is not admissible, i.e. the lack of patents does not by itself imply a lack of innovation. One reason is that many firms rely exclusively on strategic means for appropriation. Their share is also largest in the sectors with high innovation intensity, although it is rather evenly spread across the groups and excerts little discriminatory power.

{Insert about here: Figure 2. Distribution of selected firm types by the InnoType sector classification}

Apart from demonstrating the taxonomies' discriminatory power between groups, the boxplots have illustrated the prevalent heterogeneity within industries. Moreover, they give some indication about the likely causes of firm level variation. For example, Leiponen and Drejer (2007) stress three sources of firm diversity: (i) the initial heterogeneity in resources and dynamic capabilities (see, e.g., Penrose, 1959; Teece, 1983; Wernerfelt, 1984; Wernerfelt and Montgomery, 1986); [8] (ii) bounded rationality (Simon, 1957, 1959, 1979)[9] and myopic search within 'rugged' landscapes causing path dependence and lock-in to local optima (Arthur, 1994, 2009; Kaufmann, 1993; Levinthal, 1997);[10] and (iii) the deliberate strive for differentiation among firms (e.g., Caves and Porter, 1977; Tushman and Anderson, 2004).

Any of these arguments invokes a number of far reaching theoretical ideas, which would lead us too far astray for the purpose of this paper. Instead, we focus on a particular hypothesis proposed by Leiponen and Drejer (2007), which we can assess by a straightforward inspection of our data. In short,

[8] To give an example, Edith Penrose considers the diversity of firms to be characterized by a similar inimitability than individual behavior: "exactly the same resource used for different purposes or in different ways and in combination with different types or amounts of other resources provides a different service or set of services … [I]t is largely in this distinction that we find the source of the uniqueness of each individual firm" (Penrose, 1959, p.24).

[9] Models of bounded rationality acknowledge that agents are limited in their capability to process information and solve complex decision problems. The term 'complexity' relates to the interdependence among variables and can be defined by the difficulty to predict the properties of a system from the mere knowledge of the properties of its individual parts. For example, Weaver (1948) explains 'organized' complexity by "a sizeable number of factors which are interrelated into an organic whole." Relatedly, one can define complexity by the length of the shortest binary program required to solve a decision problem. For our purpose the important point is, that bounded rationality generates differential behaviour, because individual actors do not share identical information sets and/or processing routines.

[10] The term 'rugged landscapes' is used in evolutionary simulation models where interdependence parameters 'tune' the landscape of local search (see, Kauffman, 1993; Levinthal, 1991, 1997). In a frictionless selection environment, the 'fitness' parameters of surviving firms are highly correlated and single (global) optima of homogenous firms emerge over time. In contrast, if the selection environment is 'rugged', there is little or no correlation and the selection environment supports a sustained variety of local optima and viable firms.

they argue that we should find a positive relationship between the degree of variation and the overall innovation intensity in an industry, if bounded rationality and myopic search within 'rugged landscapes' are the most likely source of heterogeneity. The idea is that rapid technological change brings about an increasing complexity of search and decision processes from which the growing diversity emanates. Conversely, they argue that the lack of such a positive relationship speaks in favour of deliberate strategic decisions to differentiate and/or innate differences in capabilities, which they consider to be rather independent from the overall importance of innovation in the sector. Since they find a similar degree of variation within industries in their data, they consequently conclude that deliberate strategic differentiation and innate differences in capabilities are the primary cause of heterogeneity.

A closer inspection of the boxplots in Figure 2 reveals that the relationship between the innovation intensity of a sector and the degree of variation within each group depends on what variable we look at. If we restrict our attention to the middle 50 per cent of observations, the spread in the share of creative firms with product innovations hardly differs between the sectors characterised by low- up to medium-high innovation intensity in Panel A. However, it is substantially larger among the industries with the highest innovation intensity. In contrast, the spread in the share of non-innovating firms shows no remarkable differences between any of the groups. Similar observations apply to Panel D, where the industries with high innovation intensity exhibit the strongest divergence in the share of firms with highly cumulative knowledge. Again, the extent of heterogeneity does not differ much between the other industry types.

The same observation holds for the share of firms whose innovation activity is characterised by the mere acquisition of external knowledge in Panel B. In contrast, the extreme concentration of the high-R&D performers in the industries with high innovation intensity comes together with a huge amount of variation within that group. As discussed before, that sectors also host many creative firms which are not high-R&D performers. As a consequence, we observe almost the entire variation within that group, whereas we hardly detect any variation within the others. Finally, the diversity also grows with respect to the share of firms using patents to protect their new knowledge. But different from the previous example, the heterogeneity is continuously ascending with the innovation intensity of the respective industries, exhibiting the strongest association between level and variance among all the four variables.

On balance, our evidence favours explanations that relate firm-level heterogeneity in innovation behaviour to technological complexity, where the importance of bounded rationality, myopic search and path dependence grows with the innovation intensity of a sector. However, our findings also confirm that technological complexity cannot be the only source, since many variables show heterogeneity among the industry types with low innovation intensity. This observation calls for more generic explanations, such as strategic differentiation or the intrinsic individualism of the resource based theories of the firm, which is based on the innate diversity in preferences and capabilities as well as a profound subjectivism applied to the cognition of entrepreneurial opportunities. Both explanations apply independently to the many firms that pursue opportunities other than from technological innovation, but are likely to be reinforced by the complexity of the knowledge environment.

5. Summary and conclusions

The paper presents a new and integrated set of innovation taxonomies of firms *and* sectors. The classifications are built from the micro-data of the Third Community Innovation Survey (CIS), covering 78,000 individual firms from 22 European countries over the period 1998 to 2000. They identify firms according to Schumpeter's distinction between creative and adaptive behaviour as well three essential characteristics of technological regimes (i.e. opportunities, appropriability, and cumulativeness). The integrated approach highlights the simultaneously diverse *and* contingent nature of innovation, which contrasts the frequent evocation of an antagonism between the two. Despite the huge variety of individual innovation behaviour, the final cluster validations demonstrate that distinct technological regimes exhibit systematic differences in the distribution of heterogenous firm types.

The analysis proceeded in three stages: We first classified individual firms according to the selected innovation characteristics. In the second stage, we characterised industries by means of standardised shares of the respective firm types and then applied statistical cluster techniques to derive the respective sectoral taxonomies. In the third stage, boxplot charts validated the new classifications and provided a new and integrated picture of the variety and contingency in innovation behaviour.

The new set of classifications offers several major advances with respect to the creation of innovation taxonomies:

— First, the classifications are built on a very comprehensive set of micro-data for 22 European countries. In addition to the large sample sizes, this allows to assess the robustness of the taxonomies with respect to differences between country groups and to differentiate between economies at various levels of development.

— Second, the taxonomies apply to both manufacturing and services, treating them within a joint framework. Within the Schumpeterian research programme this is a major step forward (Drejer, 2004). Differences between manufacturing and services are not definite, but a matter of degree. To better understand them, we need a shared analytical and empirical framework as common point of reference (Windrum, 2007).[11]

— Third, the taxonomies combine an explicit theoretic rationale together with the use of appropriate statistical tools for identification. The theoretic motivation makes the results contestable, and the new types can be used as discriminatory variables in empirical tests of hypotheses received from the literature.[12] The additional use of statistical cluster techniques has the advantage of letting the data draw the boundaries between sector groups. This reduces the scope of exogenous intervention and fosters the credibility of the results.

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[11] At this point, one should mention that in this paper the spotlight on technological innovation tends to favour manufacturing industries just as the focus on formal education has favoured some service sectors in a related taxonomy of human capital (Peneder, 2007).

[12] See, e.g., the panel regressions of Peneder (2008, 2009b), where the degree of innovativeness turned out to be a remarkably robust driver of labour productivity growth over a wide range of alternative model specifications.

— Fourth, and most important, the sectors are not classified according to an industry average, but by the *distribution* of diverse firm types. As a consequence, the occurrence of innovative firms within a sector of low- or intermediate innovation intensity (or vice versa, of viable non-innovating firms within an industry characterised by high innovation intensity) is no longer an antagonism. Even though such firms are situated outside the central mass of the distribution, they are nevertheless part of it! Like all systematic deviations from a perceived norm, they constitute particularly interesting cases for study.

The results demonstrate that innovation policies must not expect homogenous firms when targeting certain industries or technologies, but address them according to their characteristic diversity and distribution in the sector. It clearly follows that we need to enhance our knowledge on both levels of observation. Good innovation policies need to be informed by an integrated perspective, which simultaneously takes account of firm-level variety and sectoral contingencies.

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Annex – Supplementary Tables and Figures

{ Insert Table A.1. The sectoral taxonomy of Schumpeterian innovation types (SpType) }

{ Insert Table A.2. The sectoral taxonomy of opportunity conditions (OpType) }

{ Insert Table A.3. The sectoral taxonomy of appropriability conditions (ApType) }

{ Insert Table A.4. The sectoral taxonomy of cumulativeness of knowledge (CuType) }

{ Insert Figure A.1. Distribution of firm types by sector classification }

Tables and Figures

Table 1: The firm sample by country and country groups

Countries	Continental	North	South	NMS10	NMS2	Total
AT	1,304					1,304
BE	1,283					1,283
DE	2,929					2,929
LU	440					440
DK		1,627				1,627
FI		1,637				1,637
IS		745				745
NO		3,623				3,623
SE		2,045				2,045
ES			8,373			8,373
GR			1,557			1,557
IT			12,964			12,964
PT			1,875			1,875
CZ				3,505		3,505
EE				2,594		2,594
HU				2,072		2,072
LT				1,954		1,954
LV				2,496		2,496
SI				2,564		2,564
SK				1,855		1,855
BG					12,758	12,758
RO					7,844	7,844
Total	5,956	9,677	24,769	17,040	20,602	78,044

Table 2: Identifying assumptions for the firm innovation types

Classification of firms	Identifying restrictions
I. Creative vs. adaptive (SpType)	
Creative ...	
... product and process innovations (CrPP)	Own process *and* product innovations (new to the market; by own firm)
... product innovations (CrPd)	Own product innovations (new to the market)
... process innovations (CrPc)	Own process innovations (developed mainly by own firm)
Adaptive ...	
... technology adoption (AdTA)	Innovation mainly by or in co-operation with other firms/institutions
... other opportunities (AdOth)	Neither process nor product innovations
II. Opportunity (OpType)	
High intramural R&D (HR&D)	Own R&D; share of innovation expenditures in total turnover > 5%
Intramural R&D (IR&D)	Own R&D; share of innovation expenditures in total turnover <= 5%
External acquisition (ACQU)	Acquisition of external R&D, machinery, rights etc.
None	Neither intramural nor external innovation activities
III. Appropropriability (ApType)	
Full arsenal (FULL)	Patents, other formal *and* strategic methods
Patents (PAT+)	Patents valid or applied (alone or with *either* formal or strategic methods)
Other formal methods (FORM)	Design patterns, trademarks, copyright (with or without strategic methods)
Other strategic methods (STRAT)	Secrecy, lead-time, complexity of design
None	No appropriation measures
IV. Cumulativeness (CuType)	
High cumulativeness of knowledge (High)	Creative firms: internal sources more or equally important than external sources; Adaptive firms: external sources more important
Low cumulativeness of knowledge (Low)	Creative firms: internal sources less important than external sources; Adaptive firms: internal sources more or equally important
None	Firms reporting neither internal nor external sources of high importance

Table 3: Crosstabulation of firm types (shares in %)

	A. Creative vs. adaptive (SpType)						B. Opportunity (OpType)					C. Appropriability (ApType)					
	CrPP	CrPd	CrPc	AdTA	AdOth	*Total*											
B. Opportunity (OpType)																	
HR&D	13.8	12.6	6.0	5.6	0.5	*3.4*											
IR&D	51.7	46.5	34.7	33.7	1.4	*14.5*											
ACQU	25.4	24.7	42.5	40.2	0.9	*11.3*											
None	9.2	16.2	16.8	20.5	97.1	*70.8*											
Total	*100*	*100*	*100*	*100*	*100*	*100*											
C. Appropriability (ApType)							**HR&D**	**IR&D**	**ACQU**	**None**	***Total***						
FULL	18.0	14.7	6.7	5.8	0.8	*4.2*	20.9	16.7	4.1	0.9	*4.2*						
PAT+	14.3	14.1	9.3	8.5	2.4	*5.4*	20.1	15.8	6.2	2.4	*5.4*						
FORM	16.4	17.5	13.2	13.8	4.7	*8.2*	16.5	18.1	13.1	5.0	*8.2*						
STRAT	18.7	18.1	18.0	14.7	4.1	*8.3*	17.7	19.9	15.1	4.4	*8.3*						
None	32.5	35.7	52.9	57.2	88.0	*73.9*	24.8	29.6	61.5	87.3	*73.9*						
Total	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*						
D. Cumulativeness (CuType)												**FULL**	**PAT+**	**FORM**	**STRAT**	**None**	***Total***
High	74.0	66.6	68.2	31.9	0.9	*19.5*	64.4	59.5	53.2	3.7	*19.5*	61.4	46.0	37.1	42.5	10.6	*19.5*
Low	23.3	28.6	24.6	59.1	1.6	*12.7*	28.8	36.6	40.3	2.7	*12.7*	27.2	25.9	24.6	25.7	8.1	*12.7*
None	2.8	4.9	7.2	9.1	97.5	*67.8*	6.8	3.9	6.5	93.6	*67.8*	11.4	28.1	38.3	31.9	81.3	*67.8*
Total	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*

Note: See Table 2 for definition of the firm-type acronyms.

Table 4: Distribution of firm types by country group in %

	Continental	North	South	NMS10	NMS2	Total
A. Creative vs. adaptive (SpType)						
CrPP	8.98	7.02	9.24	5.53	5.49	7.14
CrPd	13.01	14.89	11.13	8	5.53	9.58
CrPc	9.99	6.86	8.53	5.84	1.47	5.99
AdTA	21.54	12.46	11.16	9.79	3.21	9.72
AdOth	46.47	58.77	59.93	70.84	84.3	67.57
Total	*100*	*100*	*100*	*100*	*100*	*100*
B. Opportunity (OpType)						
HR&D	6.33	9.37	2.71	2.69	1.3	3.44
IR&D	28.86	24.7	17.26	13.13	3.26	14.47
ACQU	16.37	8.54	15.71	9.35	7.27	11.26
None	48.44	57.39	64.32	74.83	88.18	70.84
Total	*100*	*100*	*100*	*100*	*100*	*100*
C. Appropriability (ApType)						
FULL	9.79	8.47	5.65	2.1	0.69	4.23
PAT+	9.82	8.06	7.78	3.34	1.65	5.38
FORM	12.68	12.91	7.86	9.63	3.81	8.17
STRAT	12.69	10.24	11.7	8.27	2.15	8.32
None	55.02	60.32	67.02	76.66	91.71	73.9
Total	*100*	*100*	*100*	*100*	*100*	*100*
D. Cumulativeness (CuType)						
High	31.41	26.3	24.7	16.39	8.99	19.45
Low	22.9	16.79	14.39	12.34	6.12	12.71
None	45.69	56.91	60.91	71.27	84.89	67.84
Total	*100*	*100*	*100*	*100*	*100*	*100*

Note: See Table 2 for definition of the firm-type acronyms.

Table 5: The sectoral taxonomies

Nace	Industry	SpType	AcType	ApType	CuType	InnoType
10	Mining: coal, peat	TAD	ACQU	None	Low	Med-low
11	Mining: petroleum, gas	TAD	ACQU	None	Med	Med-low
14	Mining: other	Other	None	None	Low	Low
15	Food products, beverages	TAD	ACQU	FORM	Low	Med-low
16	Tobacco products	TAD	IR&D	FORM	Low	Med-low
17	Textiles	MCRE	IR&D	FORM	Med	Med-high
18	Wearing apparel, fur	Other	None	FORM	Low	Low
19	Leather, -products, footwear	Other	None	FORM	Low	Low
20	Wood, -products, cork	Other	ACQU	None	Low	Med
21	Pulp/paper, -products	MCRE	ACQU	FORM	Med	Med
22	Publishing, reproduction	TAD	ACQU	FORM	Low	Med-low
23	Ref. petroleum, nucl. fuel	MCRE	IR&D	PAT+	Med	Med-high
24	Chemicals	MCRE	IR&D	PAT+	High	Med-high
25	Rubber and plastics	MCRE	IR&D	PAT+	Med	Med-high
26	Mineral products	MCRE	IR&D	BAL	Med	Med-high
27	Basic metals	MCRE	IR&D	PAT+	High	Med-high
28	Fabricated metal products	MCRE	ACQU	None	Low	Med
29	Machinery, nec.	HCRE	HR&D	PAT+	High	High
30	Computers, office machinery	HCRE	HR&D	BAL	Med	High
31	Electrical equipment, nec	HCRE	IR&D	PAT+	High	High
32	Communication technology	HCRE	HR&D	BAL	High	High
33	Precision instruments	HCRE	HR&D	PAT+	High	High
34	Motor vehicles, -parts	MCRE	IR&D	PAT+	High	Med-high
35	Other transport equipment	MCRE	IR&D	PAT+	Med	Med-high
36	Manufacturing nec	MCRE	ACQU	BAL	Med	Med
37	Recycling	Other	None	None	Low	Low
40	Electricity and gas	TAD	ACQU	None	Low	Med-low
41	Water supply	TAD	None	None	Low	Med-low
51	Wholesale trade	Other	None	None	Low	Low
60	Land transport, pipelines	Other	None	None	Low	Low
61	Water transport	Other	None	None	Low	Low
62	Air transport	Other	ACQU	None	Low	Med
63	Auxiliary transport services	Other	None	None	Low	Low
64	Post, telecommunications	HCRE	ACQU	FORM	Med	Med-high
65	Financial intermediation	MCRE	ACQU	STRAT	High	Med
66	Insurance, pension funding	TAD	ACQU	STRAT	High	Med-low
67	Auxiliary financial services	Other	None	FORM	Low	Low
72	Computer services	HCRE	HR&D	STRAT	High	High
73	Research and development	HCRE	HR&D	PAT+	High	High
74	Other business services	MCRE	ACQU	STRAT	High	Med

Note:
SpType – *HCRE*: High creative firms with product (and process) innovations; *MCRE*: Intermediate creative frims only with process innovations; *TAD*: Adaptive firms with technology adoption; *Other*: Adaptive firms pursuing opportunities other than from technological innovation
OpType – *HR&D*: High intramural R&D (>5% of firm turnover); *IR&D*: Intramural R&D; *ACQU*: Acquisition of new knowledge (R&D, machinery, patents, etc.); *None*: No innovation activities
ApType – *PAT+*: high use of patents and other measures; *BAL*: Balanced use of various measures; *FORM:* other formal measures; *STRAT*: strategic means; *None*: no measures for appropriation
CuType – *High*: High cumulativeness; *Med*: Intermediate cumulativeness; *Low*: Low cumulativeness of knowledge.

Table A.1: The sectoral taxonomy of Schumpeter innovation types (SpType)

NACE	*Cont/North*	*South*	*NMS10*	*NMS2*	*ConClass*
10	3	4	3	4	**3**
11	3		2	4	**3**
14	4	4	2	4	**4**
15	3	2	2	3	**3**
16	3	2	1	4	**3**
17	1	2	2	2	**2**
18	3	4	4	4	**4**
19	4	4	4	4	**4**
20	4	2	4	4	**4**
21	2	2	2	2	**2**
22	3	2	3	3	**3**
23	1	2	3	2	**2**
24	2	2	2	3	**2**
25	2	2	2	2	**2**
26	2	2	2	2	**2**
27	2	2	2	3	**2**
28	2	2	4	2	**2**
29	1	1	1	3	**1**
30	3	1	1	2	**1**
31	1	1	2	2	**1**
32	1	1	2	3	**1**
33	1	1	2	3	**1**
34	2	2	1	1	**2**
35	4	2	1	2	**2**
36	2	2	2	1	**2**
37	4	4	4	4	**4**
40	4	3	3	2	**3**
41	3	2	4	3	**3**
51	4	4	4	4	**4**
60	4	4	4	4	**4**
61	4	4	3	4	**4**
62	4	2	3	4	**4**
63	4	4	4	4	**4**
64	1	4	2	3	**1**
65	2	2	2	3	**2**
66	2	3	3	3	**3**
67	4	4	4	4	**4**
72	2	1	1	1	**1**
73	1	2	1	2	**1**
74	2	2	2	2	**2**

Note: the numbers identify the sector types by characteristically high shares of …
1 = HCRE: High creative firms with product (and process) innovations
2 = MCRE: Intermediate creative firms with process innovations
3 = TAD: Adaptive firms with technology adoption
4 = Other: Adaptive firms pursuing opportunities other than from technological innovation
ConClass = 'Consensus Classification'.

Table A.2: The sectoral taxonomy of opportunity conditions (OpType)

Nace	*Cont/North*	*South*	*NMS10*	*NMS2*	*ConClass*
10	3	4	3	4	**3**
11	3		2	3	**3**
14	4	4	3	4	**4**
15	3	3	3	3	**3**
16	2	3	3	2	**2**
17	2	2	3	2	**2**
18	2	4	4	4	**4**
19	2	4	4	4	**4**
20	3	3	4	4	**3**
21	2	3	3	3	**3**
22	3	3	3	4	**3**
23	1	3	2	2	**2**
24	1	2	2	2	**2**
25	2	2	3	3	**2**
26	2	3	2	3	**2**
27	1	3	2	2	**2**
28	2	3	3	3	**3**
29	1	2	1	2	**1**
30	1	1	1	1	**1**
31	2	1	2	2	**2**
32	1	1	2	3	**1**
33	1	1	1	2	**1**
34	2	2	2	2	**2**
35	2	2	1	3	**2**
36	2	3	3	3	**3**
37	3	4	4	4	**4**
40	3	3	3	3	**3**
41	4	3	4	4	**4**
51	3	4	4	4	**4**
60	4	4	4	4	**4**
61	4	4	3	4	**4**
62	3	4	3	4	**3**
63	3	4	4	4	**4**
64	3	3	2	4	**3**
65	3	3	3	3	**3**
66	3	2	2	3	**3**
67	3	4	4	4	**4**
72	1	1	1	2	**1**
73	1	1	1	1	**1**
74	3	3	3	3	**3**

Note: the numbers identify the sector types by characteristically high shares of …
1 = HR&D: High intramural R&D (>5% of firm turnover)
2 = IR&D: Intramural R&D
3 = ACQU: Acquisition of new knowledge (R&D, machinery, patents, etc.)
4 = None: No innovation activities
ConClass = 'Consensus Classification'.

Table A.3: The sectoral taxonomy of appropriability conditions (ApType)

NACE	*Cont/North*	*South*	*NMS10*	*NMS2*	*ConClass*
10	5	5	5	5	**5**
11	1		5	5	**5**
14	5	5	5	5	**5**
15	3	3	2	3	**3**
16	3	5	3	5	**3**
17	3	3	4	5	**3**
18	3	3	5	5	**3**
19	3	3	5	5	**3**
20	5	5	5	5	**5**
21	2	1	3	3	**3**
22	3	3	2	3	**3**
23	1	1	1	1	**1**
24	1	2	1	2	**1**
25	1	1	4	2	**1**
26	1	2	2	5	**2**
27	1	4	1	2	**1**
28	4	1	5	5	**5**
29	1	1	1	2	**1**
30	4	2	3	2	**2**
31	1	1	1	2	**1**
32	1	2	4	2	**2**
33	1	1	1	2	**1**
34	1	1	1	2	**1**
35	5	1	4	1	**1**
36	2	2	4	5	**2**
37	4	5	5	5	**5**
40	5	5	5	5	**5**
41	5	5	5	5	**5**
51	5	5	5	5	**5**
60	5	5	5	5	**5**
61	5	5	5	5	**5**
62	5	5	3	5	**5**
63	5	5	5	5	**5**
64	3	5	3	3	**3**
65	4	4	5	4	**4**
66	4	4	4	3	**4**
67	3	5	3	5	**3**
72	4	4	4	3	**4**
73	1	1	1	1	**1**
74	4	4	3	1	**4**

Note: the numbers identify the sector types by characteristically high shares of …
1 = PAT+: high use of patents and other measures
2 = BAL: Balanced use of various measures
3 = FORM: other formal measures
4 = STRAT: strategic means
5 = None
ConClass = 'Consensus Classification'.

Table A.4: The sectoral taxonomy of cumulativeness of knowledge (CuType)

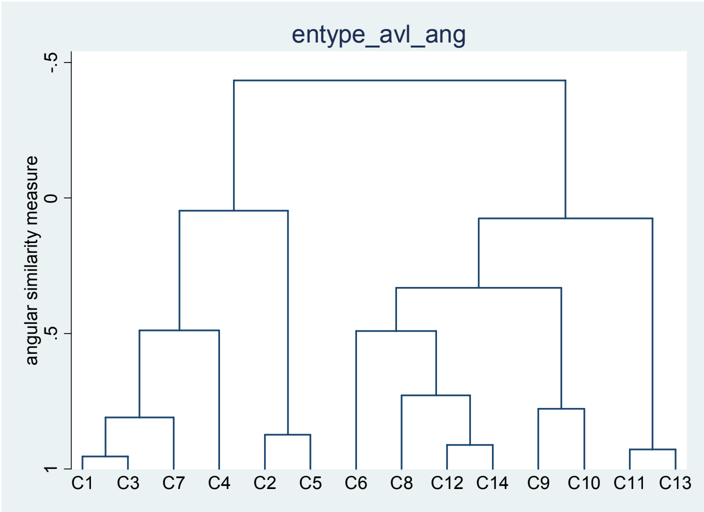
NACE	*Cont/North*	*South*	*NMS10*	*NMS2*	*ConClass*
10	3	3	3	3	**3**
11	2		3	1	**2**
14	3	3	3	3	**3**
15	3	2	1	3	**3**
16	3	3	2	2	**3**
17	1	2	2	2	**2**
18	3	3	3	3	**3**
19	2	3	3	3	**3**
20	2	3	3	3	**3**
21	2	2	2	2	**2**
22	3	2	3	3	**3**
23	2	1	2	1	**2**
24	1	1	1	1	**1**
25	1	1	1	1	**2**
26	2	2	1	2	**2**
27	1	2	1	1	**1**
28	3	1	3	2	**3**
29	1	2	1	1	**1**
30	2	1	1	2	**2**
31	1	1	1	2	**1**
32	1	1	1	2	**1**
33	1	1	1	1	**1**
34	1	1	1	2	**1**
35	3	2	1	2	**2**
36	2	2	2	2	**2**
37	3	3	3	3	**3**
40	3	3	3	2	**3**
41	3	2	3	3	**3**
51	3	3	3	3	**3**
60	3	3	3	3	**3**
61	3	3	2	3	**3**
62	3	2	2	3	**3**
63	3	3	3	3	**3**
64	2	2	1	3	**2**
65	1	1	1	1	**1**
66	1	1	1	1	**1**
67	3	3	2	3	**3**
72	1	1	1	2	**1**
73	1	1	1	1	**1**
74	2	1	3	1	**1**

Note: the numbers identify the sector types by characteristically high shares of …

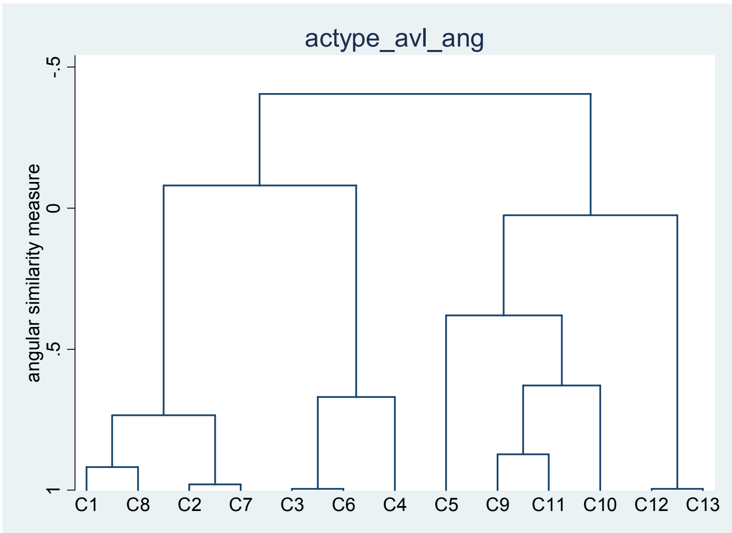
1 = High
2 = Med
3 = Low
ConClass = 'Consensus Classification'.

Figure 1: Dendrograms for average linkage method and angular separation measure

A. Sector types: creative vs. adaptive (SpType)

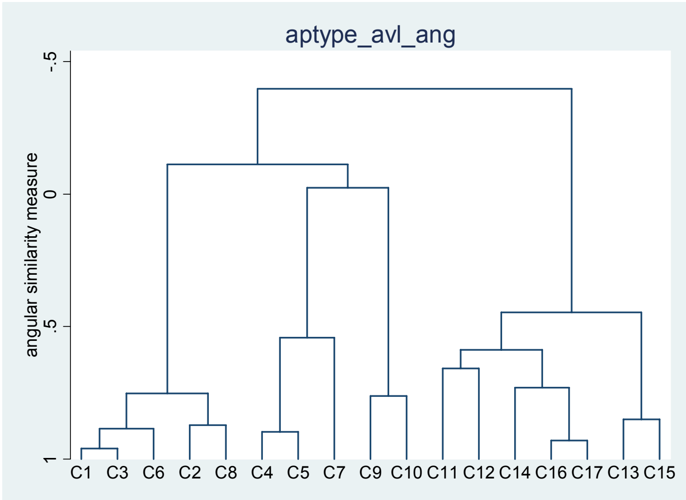


B. Sector types: opportunity conditions (OpType)

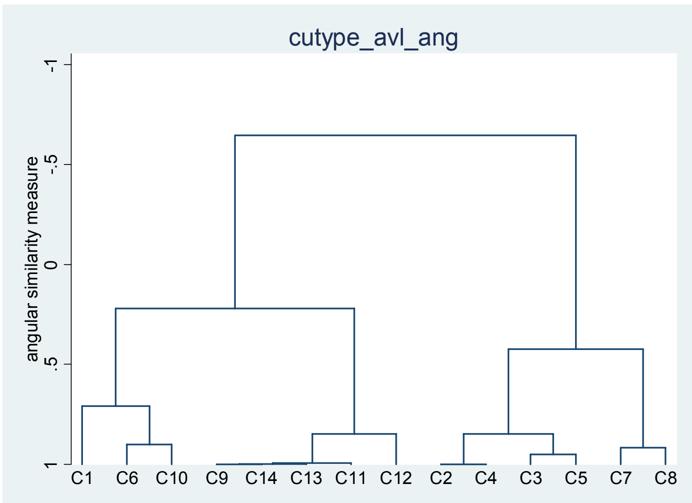


Note: Observations C1 to Cn are the solutions from the *k*-means method in the first stage of the clustering process.

C. Sector types: appropriability conditions (ApType)



D. Sector types: cumulativeness of knowledge (CuType)

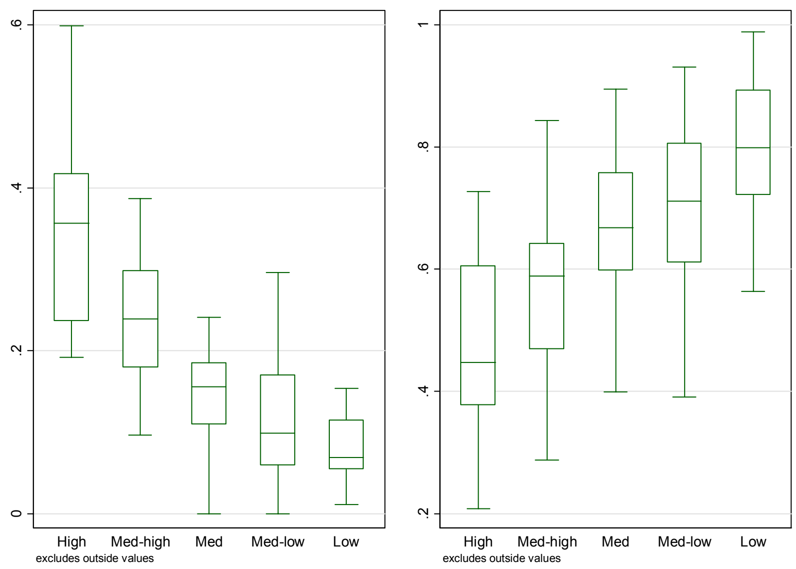


Note: Observations C1 to Cn are the solutions from the *k*-means method in the first stage of the clustering process.

Figure 2: Distribution of selected firm types by the InnoType sector classification

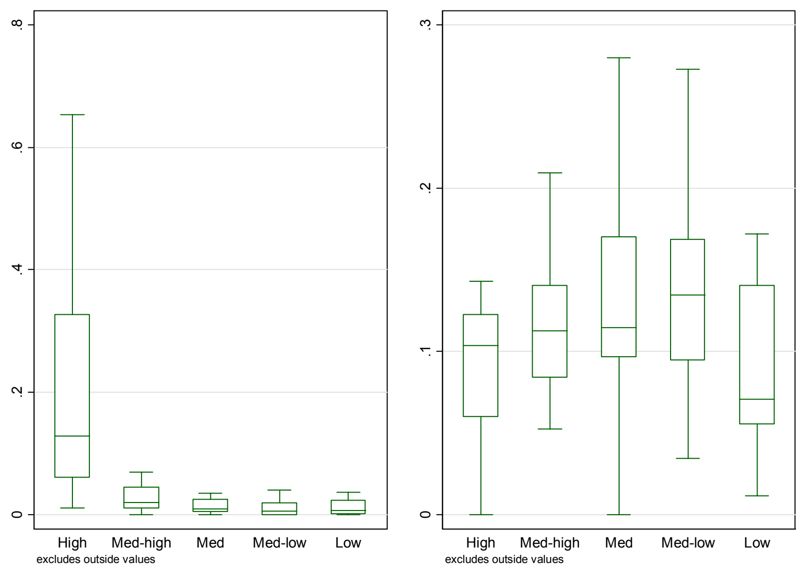
A. Firm types: creative vs. adaptive (SpType)

Product innovations (CrPP+CrPd) Other opportunities (AdOther)



B. Firm types: opportunity conditions (OpType)

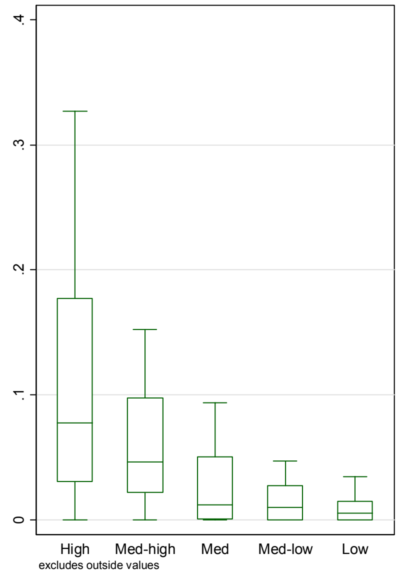
High R&D (HR&D) Acquisition (ACQU)



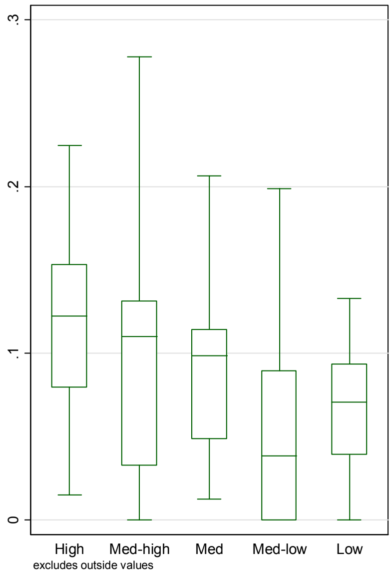
Note: The boxplots display the distribution of the specified firm types by the sector taxonomy of innovation intensity (InnoType) indicated at the horizontal axis.

C. Firm types: appropriability conditions (ApType)

Patents (PAT+)

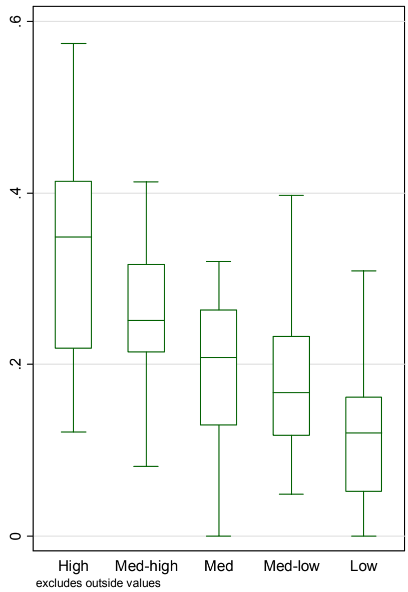


Strategic (STRAT)

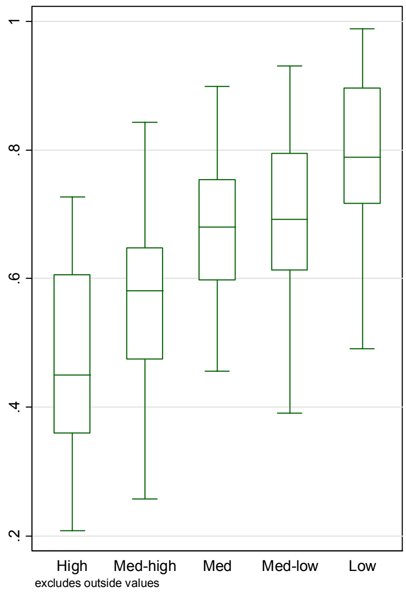


D. Firm types: cumulativeness of knowledge (CuType)

High cumulativeness



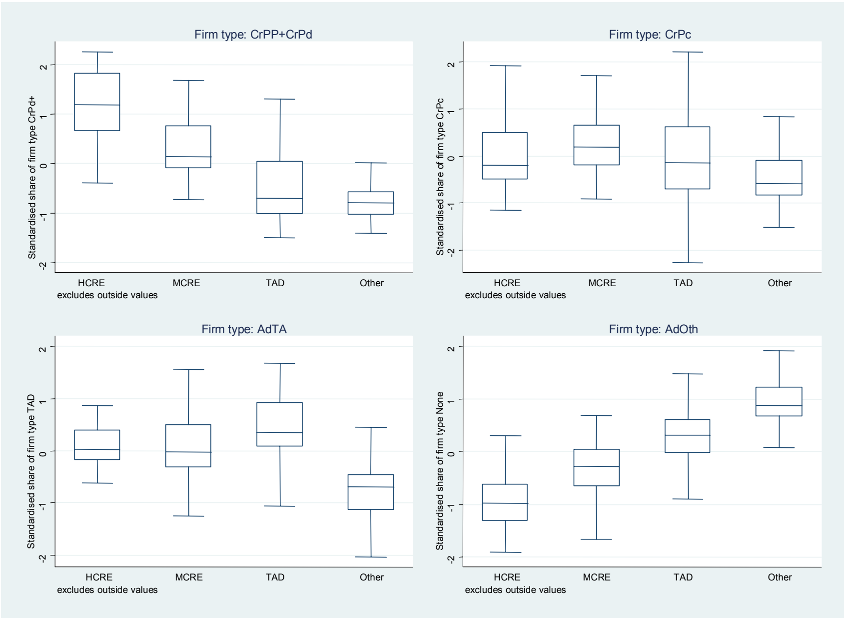
None



Note: The boxplots display the distribution of the specified firm types by the sector taxonomy of innovation intensity (InnoType) indicated at the horizontal axis.

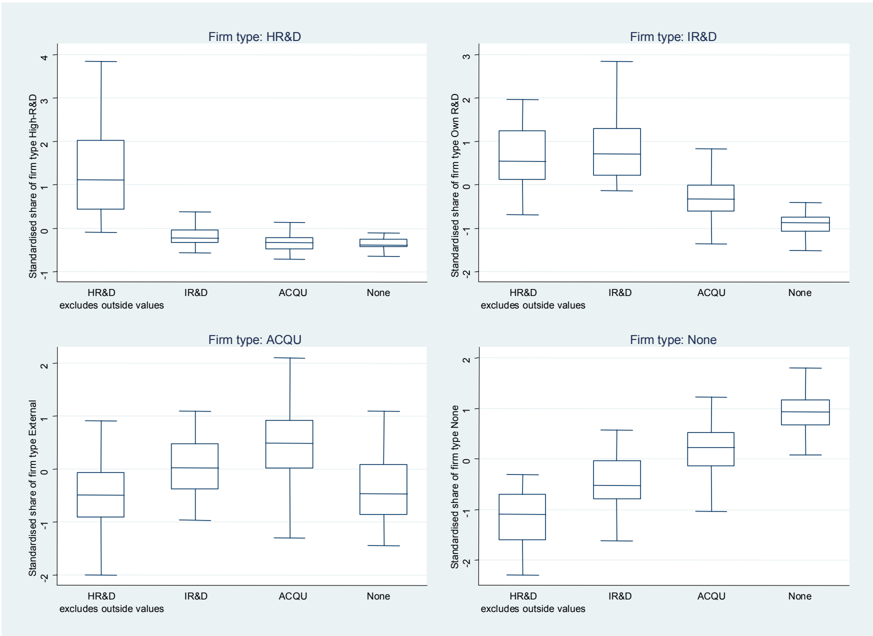
Figure A.1: Distribution of firm types by sector classification

A. Firm and sector types: creative vs. adaptive (SpType)



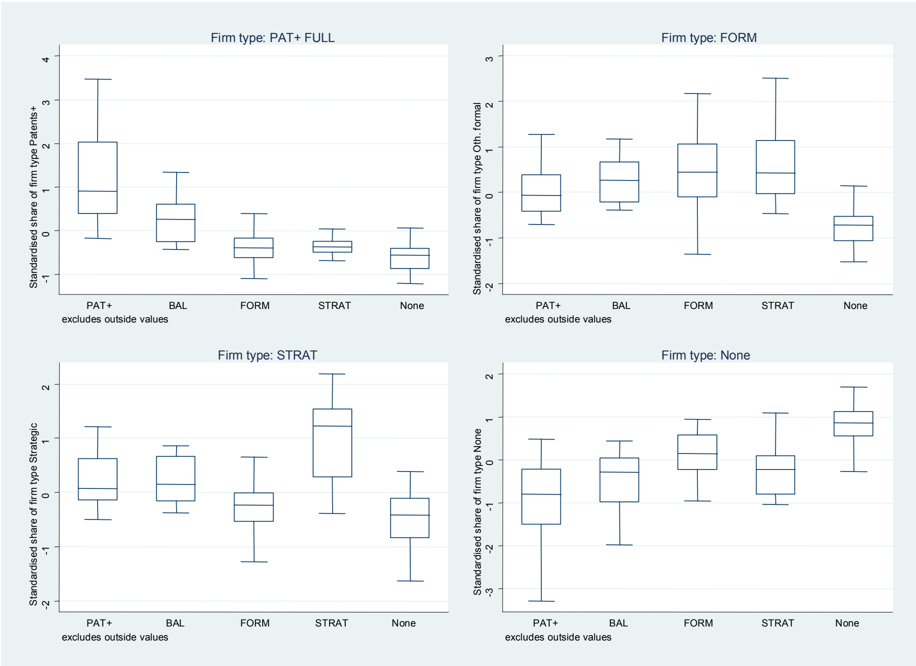
Note: The boxplots display the distribution of the specified firm types by sector types (indicated at the horizontal axis).

B. Firm and sector types: Opportunity conditions (OpType)



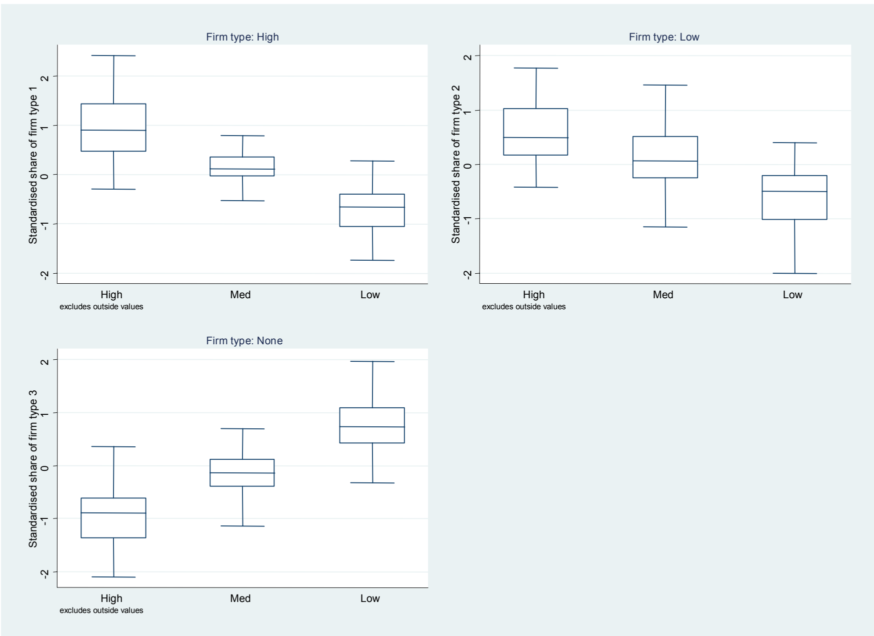
Note: The boxplots display the distribution of the specified firm types by sector types (indicated at the horizontal axis).

C. Firm and sector types: Appropriability conditions (ApType)



Note: The boxplots display the distribution of the specified firm types by sector types (indicated at the horizontal axis).

D. Firm and sector types: Cumulativeness of knowledge (CuType)



Note: The boxplots display the distribution of the specified firm types by sector types (indicated at the horizontal axis).

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