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Entrepreneurship, technological regimes, and productivity growth

Integrated taxonomies of firms and sectors

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ABSTRACT

This research is aimed at the interlinkages between the micro-and the meso-level of innovation. It focuses first on heterogeneous innovation behaviour among individual firms, and then derives new taxonomies from the distribution of distinct firm types within sectors. The outcome is a set of integrated classifications both at the firm and sectoral levels, which focuses on (i) the kind of entrepreneurship; (ii) technological opportunity; (iii) appropriability conditions; (iv) the cumulativeness of knowledge, and (v) a sector's general 'innovation intensity'. Final validations of the clusters confirm, e.g, a significant positive but non-linear impact of a sector's innovation intensity on labour productivity growth.

Key Words: Entrepreneurship, technological regimes, productivity growth, sectoral taxonomy, industry classification.

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 and capabilities among individual companies. At the same time, sectoral data repeatedly demonstrate persistent and significant differences (e.g., with respect to average factor intensities, firm duration, etc.) between sectors. 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 most empirical analyses, this tension remains unresolved. The variety of firm behaviour causes many researchers to focus on micro-data, frequently discarding the more aggregate levels of analysis. Conversely, persistent differences between sectors draw much attention towards sectors, where observed regularities are often interpreted as if there were no variety within them. What is largely missing, however, is an integrated perspective, which simultaneously takes account of firm-level variety and sectoral contingencies. Building an integrated set of new innovation classifications for firms and sectors from a joint micro-datasource, that is precisely where this paper aims to make a contribution.

One can distinguish two major reasons for the creation of industry classifications: First, from an analytical point of view, sectoral taxonomies facilitate investigations into the impact of specific characteristics of the market environment on economic activity. Substituting structural knowledge for exhaustive information concerning single attributes, the intractable diversity of real-life phenomena is condensed into a smaller number of salient types. Classifications thus direct our attention towards a few characteristic dimensions, according to which relative similarities or differences can be identified. They allow us to take account of heterogeneity, while simultaneously forcing us to be selective. Secondly, from a purely practical perspective, the taxonomic approach is particularly useful when referring to data that are not easily available in a comparable format across countries or firms. The reason is that it builds upon data from those entities, which offer the best coverage of specific attributes and then produces typical profiles of the relevant variables. The resulting classification can then be applied to other data on economic activity, which is available on a broader comparable basis (e.g., value added, employment, or labour productivity).

A number of innovation taxonomies already exists, from which Pavitt (1984) and Hatzichronoglou (1997) stand out as the best known and most influential examples. Furthermore, there are many others (see Section 2.2), which leads to the question why we should long for yet another innovation classification? The first and most obvious reason is the availability of new data. More specifically, this paper taps the micro-data from the newly established Eurostat Safe Center, which provides access to CIS firm level data for a considerable range of European countries. With a huge number of individual observations at hand, the empirical basis for the new taxonomies offers a wealth of opportunities to test new ideas. Second, the methods of classification have only recently begun to capture a noticeable share of debate among economists. In contrast to the attention given to the tremendous mass of econometric literature, the proper construction and use of classifications has remained largely under-researched within the realm of economics. Many taxonomies lack a theoretical justification and are purely data driven, while others suffer from *ad hoc* methods of empirical identification, missing out on the available statistical toolbox. Fortunately, the degree of sophistication aspired in the creation of industry classifications is gradually growing (Peneder, 2003, 2007a). One of the intentions of this paper is to provide an example of good practice –in terms of both the theoretical justification and the methodological rigour that can be applied to the classification process.

When more than one taxonomy cover a similar topic, the frequently encountered question ‘but which is the correct one?’ proves how widespread the lack of understanding still is. Any classification is a social construct that emanates from a specific context of use, availability of data, and methodology. There is neither much objective ground for, nor meaning in ranking them against each other. However, some benchmark criteria do exist, and it is against them that a new taxonomy ought to prove its worth:

— First of all, industry classifications ought to have an economic rationale in the sense that they relate to theoretical concepts and categories. Apart from being a general attitude (which one may or may not share), this has the practical advantage that new taxonomies can be used as discriminatory variables in empirical tests of hypotheses received from the literature.

— Secondly, the taxonomies must prove their discriminatory power with respect to the variables chosen for the classification process. Rather than being trivial, this is to say that the objects being classified must exhibit true structural differences.

— Finally, the taxonomies should be able to discriminate significantly along dimensions other than those already applied in the classification process. Even though this is not a definite requirement for validation, it demonstrates its usefulness for further analytical purposes.

This is the third in a series of papers producing new sectoral classifications, all of which aim to stand their ground with respect to the above criteria. All three apply the same approach to statistical cluster analysis and target the NACE 2-digit level of industry disaggregation, comprising both the manufacturing and the services sectors. The two previous papers focused on the sectoral characteristics of educational intensity (Peneder, 2007b) and firm demography (Peneder, 2008). None of them offered the opportunity to investigate the interlinkages between firm-level variety and sectoral contingencies, which is unique to the research pursued in this paper.

The research plan comprises three consecutive parts. In the first stage, we focus on heterogeneity among firms. Characterising firm types with respect to innovation behaviour, we take on two analytical themes that appear in distinct strands of economic literature. One emphasis is on *entrepreneurship*, where we distinguish different ways of how firms pursue opportunities to make a profit and which relate to innovation in varying kinds and degree. Another emphasis is on *technological regimes*, which highlight intrinsic differences in the knowledge environment between sectors that are supposed to constrain available options for firm behaviour (Malerba and Orsenigo, 1993). Each subsection begins with a brief theoretical discussion and then explains the empirical strategy for identifying firms to particular innovation types. In the second stage, we classify industries by the relative distribution of the firm types previously identified. In contrast to the direct categorisation of firms by means of specific rules of identification derived from the theoretical literature, we now ‘let the data speak’ and apply statistical cluster algorithms to detect the structural differences between sectors. In the final stage, we validate the new taxonomies and test for their discriminatory power, first in terms of the distribution of firm types within sector classes, and then by applying them to a set of panel regressions explaining the sectoral growth of labour productivity. While the former demonstrate the simultaneous interplay between firm heterogeneity and sector contingencies, the latter provides an illustrative example for the general usefulness of the new taxonomy in applied empirical research.

The new classifications are based upon the micro-data of the Third Community Innovation Survey (CIS3), which was made available by Eurostat through its newly established Safe Center. These data cover the innovation activities of more than 78,000 firms from 22 European countries over the period 1998 to 2000.[1] 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 panel design. More generally, one must also be prepared to find a considerable amount of unsystematic noise in the individual data, especially with respect to questions, for which it is difficult to define any general objective criteria for assessment.

In order to increase the sample sizes per sector and render our sectoral results more robust, we aggregate the data by broad country groups in the second stage of the classification process. We thereby 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 reports the sample sizes by country and country groups.

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

The remainder of this paper is organised according to the three stages of research as sketched above. Section 2 explains the theoretical rationales and rules for the empirical identification of innovation types at the firm-level. Section 3 discusses the statistical cluster analysis and presents the new sectoral taxonomies. Section 4 validates the final cluster solutions, while Section 5 summarises and concludes.

2. Identification of firm types

2.1 Entrepreneurship

Despite the variety of theories and definitions, a common emphasis on opportunity seeking behaviour has emerged as the core element in most of the contemporary literature on entrepreneurship. For example, we find that in the widely used textbook by Sahlman et al. (1999, p. 7), where entrepreneurship is defined as ‘the pursuit of opportunity without regard to resources currently controlled’. Similarly, Venkataraman (1997, p. 120) states that ‘entrepreneurship as a scholarly field seeks to understand how opportunities to bring into existence “future” goods and services are discovered, created, and exploited, by whom, and with what consequences’. Further elaborating this approach, Shane and Eckhardt (2003, p. 165) define entrepreneurial opportunities ‘as situations in

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[1] We use the third survey (CIS3) because it is the most recent one for which the EUROSTAT Safe Center has cleared access to firm-level data.

which new goods, services, raw materials, markets and organising methods can be introduced through the formation of new means, ends, or means-ends relationships.' However, establishing a more specific relationship between entrepreneurship and innovation behaviour can best be achieved through distinguishing three functions, which are heralded in different strands of the literature, namely the Austrian theory of market co-ordination, the human capital theory of imitative entrepreneurship, and the Schumpeterian theory of endogenous innovation (see Peneder, 2006).

Market co-ordination

The modern concept of entrepreneurial competition as an opportunity seeking discovery process has its origins in the Austrian school of economics, which progressively developed the idea of the informational function of market prices and the related entrepreneurial task of processing information about the conditions of demand and supply. Hayek (1945, 1978), in particular, explained how the competitive process stimulates the discovery of profit opportunities through the information revealed by movements in the price system. It is the entrepreneurial discovery of variations in prices that incites a business owner to increase supply where shortages of a particular commodity are most severe. The same entrepreneurial *alertness* to price signals causes continuous adjustments in the allocation of resources between competing uses (Kirzner, 1997). In other words, entrepreneurs enhance the process of market co-ordination, but otherwise have no specific connections to innovation activities per se.

Technology adoption

An alternative perspective was championed by the founder of human capital theory, Theodore Schultz (1975), who highlights the entrepreneurial function of enhancing efficiency through moves towards the current technology frontier. This frontier is continuously upset by exogenous changes, for example from publicly funded R&D or innovations produced in other sectors of the economy. Schultz thus draws our attention to what we may call 'imitative entrepreneurship' and its importance for the adoption and wide-spread diffusion of new technologies. Being mainly interested in the explanation of occupational choices, Schultz postulates the 'ability to deal with disequilibria' as the distinguishing personal characteristic of entrepreneurs. Arguing that this ability can be enhanced by education and experience, he also emphasises the particular responsibility of educational policies.

Among later writers, Baumol (1993) stresses the role of entrepreneurial initiative in the process of technology adoption. Within the strand of human capital theory, Schmitz (1989) builds strongly on the notion of imitative entrepreneurship, assuming exogenous opportunities which continuously arise in the form of disequilibria.

Endogenous innovation

Finally, the entrepreneurship theory by Joseph Schumpeter (1911, 1938) heads in a different direction by stressing endogenous innovation as its defining characteristic. For Schumpeter (1911, 1938. entrepreneurship is the particular economic function responsible for introducing novelty to the system and thus driving economic change. Schumpeter consequently separates entrepreneurship from other economic functions, which may or may not be fulfilled by the same individual, e.g. the capitalist function (characterised by the 'ownership of means'); management (the 'administration of a going concern'. or the inventor (who 'produces ideas'). Each of these functions constitutes an analytically separable source of income. Someone who is simultaneously an inventor, owner, and manager of a business draws on all of them. The particular earnings that accrue to the entrepreneurial function are the rents attributable to the (temporary) monopoly position established through successful innovation.

As is well known, Schumpeter distinguished five different kinds of innovation. For the purpose of the current research, we will focus only on technological innovation by means of introducing either new products or new processes, leaving aside the pursuit of new resources, new markets, or new forms of industrial organisation.

Empirical implementation

To summarise, all three theories of entrepreneurship share a dynamic view of markets being persistently out of equilibrium. However, the Austrian School and the theory developed by Theodore

Schultz focus on equilibrating tendencies caused by the entrepreneurial pursuit of profit opportunities in response to exogenous disturbances, whereas Schumpeter championed a diametrically opposite view, with the entrepreneur being the principal 'agent of change' (Audretsch, 1995) in the economy.

Apparently, each of the three economic functions of market co-ordination, technology diffusion, and innovation originates in the entrepreneurial pursuit and exploitation of opportunities to make a profit. Hence, they are all consistent with the aforementioned general behavioural definition of entrepreneurship. Still they are fundamentally different. Following the terminology formulated by Schumpeter (1947), endogenous innovation represents a 'creative response', while market co-ordination and technology adoption are two distinct forms of 'adaptive response' to the challenges posed by a dynamic market environment.

Based on these considerations, the empirical identification of different types of entrepreneurship among the firms sampled in the European Community Innovation Survey turns out to be surprisingly straightforward:

— *Creative entrepreneurs*, as defined by Schumpeter, are characterised by own innovations. For the purpose of this study, we further distinguish between 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 as *adaptive entrepreneurs*. Among them we further identify the group of *technology adopters* (AdTA), which is motivated by Schultz' entrepreneurship theory 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.

— Finally, there is a large residual group of adaptive entrepreneurs that pursue *opportunities other than from technological innovation* (AdOth). These may originate in pure market co-ordination (in the sense of Hayek and Kirzner) as well as from non-technological innovations (e.g. in terms of exploiting new resources, markets, or industrial organisation in the sense of Schumpeter's broader definition of innovation).[2]

2.2 Technological regimes

In contrast to the prevalent individualism of entrepreneurship theories, the concept of technological regimes (Nelson and Winter, 1982; Winter, 1984; Malerba and Orsenigo, 1993) points at the intrinsic differences between technologies, claiming that firms operating within the same regime are likely to share some proximate organisational and behavioural features (Dosi and Malerba, 1996). In the words of Winter (1984, p. 293)

> "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'."

In the same year, Pavitt (1984) 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. Since the 1990s, the availability of firm data from national innovation surveys induced several papers which relate to the tradition of the Pavitt classification, but are more 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 firm level. Examples are Cesaratto and Mangano (1993), Arvanitis and Hollenstein (1998), Hollenstein (2003), or Arundel and Hollanders (2004). Among sectoral

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[2] Forming classes which are mutually exclusive, the identification also requires a certain order among these rules. This implies, for example, that firms which simultaneously adopt external technologies and generate their own innovations are

classifications in the tradition of Pavitt's taxonomy, the most refined example is *Marsili* (2001). Other notable examples are *Evangelista* (2000), who was probably the first to apply Pavitt's approach to the services industries, and deJong and Marsili (2006).

In contrast to most of the above examples, this paper departs from the endurable but well-worn trails followed by Pavitt (1984). Instead, the focus is on the theoretical concept of technological regimes as introduced by Malerba and Orsenigo (1993). They characterise technological regimes very specifically in terms of *opportunity*, *appropriability*, and *cumulativeness*, the combination of which defines the knowledge and learning environment within which a firm operates. Abstract as these concepts may appear, the following arguments demonstrate the possibility of relating them to the empirical data available from the CIS surveys. Table 2 summarises the rules for identifying the new firm-level types.

{Insert Table 2: Entrepreneurship and innovation types: identifying assumptions}

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 turnover. However, 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).

classified within the group of creative entrepreneurs.

However, opportunities cannot be explained solely by technology. Opportunities 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).[3]

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 perceived technological opportunities revealed by the particular innovation activities:

— *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.

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

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[3] 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'.

informal means at hand with 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 entrepreneur's specific innovation.

The CIS offers a comprehensive set of tools 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.[4]

Cumulativeness

Our third characterisation 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

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[4] 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.

environments characterised by increasing returns" to knowledge creation (Malerba and Orsenigo, 1993, p.49).[5]

Given the rather 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 was characterised as a 'creative entrepreneur' in Section 2.1, 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 entrepreneurship', 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.

While these rules may seem rather complex at first sight, they follow from one straightforward consideration. If knowledge is highly cumulative, creative entrepreneurs, 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 entrepreneurs, 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

[5] Cumulativeness and appropriability conditions are related, but nevertheless different concepts. Consider, e.g., how appropriability conditions feature prominently in static welfare analysis (external effects. whereas cumulativeness refers to dynamic properties of a system, such as path dependence and lock-in effects.

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 entrepreneurs, whose aim is to catch-up and reduce the technology gap.

Interrelationships among firm types

It is apparent from the above discussion that the various dimensions are interrelated. Table 3 therefore provides additional detail on the pairwise co-identification of firms in the different taxonomies. Overall, the shared properties appear reasonable and consistent with *a priori* expectations. For example, firms characterised as either intramural or even high R&D performers exhibit the highest share of creative entrepreneurs doing product innovations. Conversely, firms that innovate primarily through the acquisition of new technology exhibit the highest share of firms depicted as process innovators or technology adopters. Similarly, the share of firms using patents is highest among creative entrepreneurs, followed by technology adopters and finally the firms pursuing opportunities other than from innovation. Also, the cumulativeness of knowledge is largest among creative entrepreneurs and high R&D performers, whereas the share of firms operating within a regime of low cumulativeness is largest among technology adopters and firms pursuing opportunities through the acquisition of new technology.

{Insert Table 3: Distribution of firm types by country group in %}

In addition to this overall consistency of firm types, the crosstabulation also demonstrates that each taxonomy represents an independent analytical dimension (as supposed, e.g., 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.

Finally, Table 4 compares the share of firm types with respect to the five broad country groups. In addition to the considerable heterogeneity between countries, the table displays a consistent congruence in the relative importance of firm types that relate to ‘more innovativeness’ with higher levels of economic development (e.g., GDP per capita). For example, we find considerably higher shares of creative entrepreneurs 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 Table 4: Crosstabulation of firm types (shares in %)}

3. The sector taxonomies

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

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.[6] 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:

(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 Figure 1: Dendrograms for Average Linkage Method and Angular Separation Measure of Similarity }

6 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" (see Peneder, 2001).

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 Table 5: The new 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 not meant to be the culmination of the others. It rather represents a simplification that might 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, 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 entrepreneurship 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 entrepreneurship mostly involved in process innovations, and many firms performing R&D, albeit less than 5% of turnover. Cumulativeness of knowledge is high or intermediate and patents are frequently used for appropriation. Examples are chemicals, motor vehicles, other transport equipment, or telecommunication and postal services. The latter is distinctly characterised by high creative entrepreneurship 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 adaptive entrepreneurship, pursuing opportunities through the adoption of new technology. Accordingly, the prevalent mode of innovation activity is the acquisition of new technology. Appropriability conditions are generally 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 entrepreneurs pursuing opportunities other than from new technologies, typically performing no innovation activities nor applying any measures for appropriation. The cumulativeness of knowledge is low or irrelevant, since no information regarding innovations is pursued. Examples are wearing apparel, leather products, recycling, as well as wholesale trade and land and water transport.

4. Cluster validation

4.1 The distribution of firm types within sector classes

For the purpose of cluster validation, the boxplots in Figure 2 and Figure A.1 (in the Annex) provide us with an integrated view, displaying the differences in the shape and dispersion of firm types between the various sector types. The boxplots are also evidence of the degree of discrimination between the different categories and allow us to assess the accurateness of our interpretation. The charts are easy to read. The box itself comprises the middle 50 percent 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 best summarise the integrated perspective of firm-type variety 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 entrepreneurs doing product innovation for the different categories of the EnType classification. 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. For appropriability conditions (Panel C), the share of firms applying patents to protect their innovations peaks in the according class of sectors, and then decreases continuously. 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 firm level taxonomies across the categories formed in the final sectoral classification of innovation intensity (InnoType). For example, we find an almost linear positive association between the degree of innovativeness in the sector and the share of firms characterised as creative entrepreneurs, carrying out product innovations (Panel A.a), firms applying patents (Panel C.a), and firms experiencing a high cumulativeness of knowledge (Panel D.a). In contrast, firms pursuing opportunities by means of high R&D expenditures are extremely concentrated among the sectors classified as highly innovative (Panel B.a). The share of firms pursuing opportunities through the acquisition of new technology peaks in the categories of intermediate and intermediate-to-low innovativeness (Panel B.b). The share of firms applying only strategic measures for appropriation is relatively evenly spread across the distinct sector classes (Panel C.b). Finally, the figures reveal consistent negative associations with respect to the share of entrepreneurs pursuing opportunities other than in innovation (Panel A.b) and for firms operating with more or less common knowledge about their technologies (Panel D.b).

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

4.2 Labour productivity growth

In this section, we want to put the new sector classification of innovation intensity (InnoType) to a final test by applying its classes as explanatory variables within a joint set of panel regressions, while the sectoral growth of labour productivity is implemented as a dependent variable. In contrast to the previous boxplots, this is not a validation in its strict sense. Since the clustering procedure was not aiming at grouping industries according to their productivity performance, one cannot judge the quality of the classification process dependent on this outcome. However, by testing whether the new taxonomy exerts a significant and robust impact within a joint and reasonable econometric model, we aim to demonstrate its usefulness for further empirical analyses.

More specifically, we ask whether sectors characterised by a distinct innovation intensity differ in their contributions to the average growth of labour productivity. It is for this purpose that we build a two-way data panel made up of sectors *i* in countries *j* as independent observations, while all performance variables refer to average values over the period 1995 to 2004. The econometric model thus estimates the impact of *k* sector types, *n* additional control variables *x*, and the fixed country effects *j* on the performance variable y_{ij}:

(4) $$y_{ij} = c + \alpha_k InnoType_k + \sum_n \beta_n x_n + \gamma_j + \varepsilon_{ij}$$

In the baseline specification, the fixed country effects control for all constant differences between countries that are not captured by the other explanatory variables. Among the control variables *x*, we include in each of the estimated models the logarithm of the sector's initial level of labour productivity in 1995 to control for catching-up effects. We further take into account differences in capital intensity, by including the mean and log change of the share of capital in total factor income.

For a number of other explanatory variables, multicollinearity and the additional loss of observations bars us from including all of them within one integrated model. We therefore apply separate specifications to test how robust the growth impact of the InnoType taxonomy is to the inclusion of the share of information and communication technologies (ICT) in total capital income, the average share of high-skilled labour in total hours worked, firm turnover (as a proxy for 'creative destruction'), average firm size, the average Herfindahl-Hirschman concentration index (HHI), or measures of export openness and import penetration.

All the three performance measures, as well as those on (ICT) capital and high-skill labour inputs, are extracted from the EU KLEMS database of sectoral accounts for productivity analysis (see O'Mahony, Rincon-Aznar, and Robinson, 2008).[7] The control variables on firm turnover, average firm size and market concentration are based on Eurostat's Structural Business Statistics (see Hölzl and Reinstaller, 2008). The data on export and import openness originate in the UN Comtrade database (see Sieber and Porto, 2008).

With the exception of the average capital share in factor income and the average firm size, all the variables are expressed in logarithm. We generally expect the control variables *x* to be 'growth drivers' with an accordingly positive coefficient in the estimations. Two exceptions are the initial level of labour productivity and industry concentration. Considering them to be 'growth barriers', we expect negative signs. Another exception is average firm size, where we find no strong *a priori* reasoning for either a positive or negative impact.

Table 6 reports the estimation results. To begin with, specifications (1) and (2) compare two alternative baseline models. The first model is with fixed industry effects for each NACE 2-digit sector, while the second replaces them with the new sectoral taxonomy (InnoType). The overall variation explained by the model is of course higher when we use fixed industry effects, because of the larger number of dummy variables. All coefficients for the industry-type dummies need to be interpreted relative to the group of sectors with a 'high innovation intensity', which is used for a comparative control.

In short, the estimates show a significant positive but not necessarily linear relationship between an industry's innovation intensity and labour productivity growth. It is in particular the group of sectors classified as 'highly innovative' which consistently outperforms the others. In contrast, the sectors characterised by an 'intermediate-to-low innovation intensity' often perform worse than those classified in the group with 'low innovation intensity'. This indicates that the sectors with the lowest innovation intensity are capable of exploiting opportunities from sources other than technological innovation in order to expand demand and output.

{Insert Table 6: Innovation intensity and labour productivity growth, 1995-2004 (t-value in brackets)}

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[7] For further information, data access and a detailed methodological description see Timmer, O'Mahony and van Ark (2007) available at http://www.euklems.net.

Apart from offering a deliberate economic interpretation, another advantage of applying the sectoral taxonomy in place of the fixed industry effects is the considerable degrees of freedom thus saved. These pay off, when the baseline model is extended by the other independent variables in the specifications (3) to (9). Being significant and displaying the expected impact on sectoral growth, the additional control variables live up to expectations. The pleasant surprise, however, is that the InnoTypes prove to be extremely robust to the inclusion of these additional control variables. Not only are the coefficients significant across a wide range of different model specifications, also they exhibit identical signs and relatively small variations in size.

5. Summary and conclusions

This paper presents an integrated set of taxonomies of firms and sectors and focuses on the distinction between creative and adaptive entrepreneurship, as well as the varying kinds and degree of technological opportunities, appropriability conditions and cumulativeness of knowledge. The new taxonomies are built from the micro-data of the Third Community Innovation Survey (CIS3) and cover 22 European countries.

The analysis proceeded in three stages: It first classified individual firms according to selected innovation characteristics, which are based on rationales derived from entrepreneurship theory and the literature on technological regimes. In the second stage, the paper characterised NACE 2-digit 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 and panel growth regressions validated the new classifications. The former provides a window through which we can glance at the distribution of firm types within sector classes, while the latter proves that the innovation intensity of a sector does have a significant impact on labour productivity growth.

In short, the new classification system offers three major strengths:

— First, the taxonomies combine an explicit theoretic rationale together with the use of statistical tools for final identification. The theoretic motivation makes the results contestable and eases further progress through cumulative improvements. In addition, the new types can be used as discriminatory variables in empirical tests of hypotheses received from the literature. 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 final results.[8]

— A second major strength is the joint classification of firms and industries. Apart from extending the theoretic motivation from the firm to the sector level, the new sector types are identified by the *distribution* of firms (and not, e.g., by an industry average that may be misinterpreted as being representative). This eases the apparent tension between firm variety and sector contingencies. For example, the frequently cited observation of a highly innovative firm within an industry characterised by low innovativeness (or vice versa, an imitating firm competing successfully in an industry with much creative entrepreneurship) does no longer contradict or compromise the validity of the sector type. While it is true that such firms are situated outside the mode of the distribution, they nevertheless are part of it and can be particularly interesting cases to study (see, e.g., von Tunzelmann and Acha, 2005).

— Finally, the new taxonomies apply to both manufacturing and the services sectors, treating them within a joint analytical framework.

Nevertheless, one must stress that this paper is only an early travelogue on the longer road before us. Among others, future research will have to explore and advance along the following directions:

— First, we need to extend the analysis to additional aspects of innovation behaviour, such as organisational change, or modes of co-operation and networking. For example, the focus on

[8] A direct theoretical rationale seemed more appropriate with respect to micro-behaviour, and we therefore did not apply statistical cluster analysis for the identification of firm types. Using their share as the input for the statistical clustering of sectors, this had the additional

technological innovation in the current attempt may put the services sectors at a certain disadvantage in terms of their attributed degree of 'innovativeness'. If that is true, one will ultimately need new or more precise analytical categories that better capture the nature of innovation in services.

— Second, starting from the micro-data, the approach allows us to increase the degree of disaggregation, e.g., to the level of NACE 3-digit industries. However, one must be careful about small sample sizes, which are likely to affect the robustness of the results.

— Third, it would be desirable to further extend the number of observations. For example, in order to test the robustness of the sector types over time, the analysis should be updated as soon as Eurostat clears the micro-data for the recent waves of the CIS. Also, several important countries such as France and the UK are missing from the Eurostat files. One can only hope that these data are also cleared by the national statistical institutes, in which case they can be included and clustered jointly with the other European countries.

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advantage that the interpretation of the final industry classifications remained relatively straightforward. The exogenous rules for identification in the first stage had thus been necessary to allow for a precise interpretation of the final sector types.

accessible their extractions from the UN Comtrade database. Finally, the paper has benefited from manifold constructive comments and suggestions, most notably by Werner Hölzl, Jürgen Janger, Andreas Reinstaller, and Hugo Hollanders.

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Annex – Supplementary Tables and Figures

{Insert Table A.1: The sectoral taxonomy of entrepreneurship types (EnType)

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

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

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

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

Tables and Figures

Table 1: The firm sample by country and country groups

Nuts_2dig	Continental	North	South	NMS10	NMS2	Total
AT	1,304	-	-	-	-	1,304
BE	1,283	-	-	-	-	1,283
BG	-	-	-	-	12,758	12,758
CZ	-	-	-	3,505	-	3,505
DE	2,929	-	-	-	-	2,929
DK	-	1,627	-	-	-	1,627
EE	-	-	-	2,594	-	2,594
ES	-	-	8,373	-	-	8,373
FI	-	1,637	-	-	-	1,637
GR	-	-	1,557	-	-	1,557
HU	-	-	-	2,072	-	2,072
IS	-	745	-	-	-	745
IT	-	-	12,964	-	-	12,964
LT	-	-	-	1,954	-	1,954
LU	440	-	-	-	-	440
LV	-	-	-	2,496	-	2,496
NO	-	3,623	-	-	-	3,623
PT	-	-	1,875	-	-	1,875
RO	-	-	-	-	7,844	7,844
SE	-	2,045	-	-	-	2,045
SI	-	-	-	2,564	-	2,564
SK	-	-	-	1,855	-	1,855
Total	5,956	9,677	24,769	17,040	20,602	78,044

Table 2: Entrepreneurship and innovation types: identifying assumptions

Classification of firms	Identifying restrictions
I. Entrepreneurship type (EnType)	
Creative ...	
... product and process innovations (CrPP)	Own process *and* product innovations (new to the market; by own enterpr.)
... product innovations (CrPd)	Own product innovations (new to the market)
... process innovations (CrPc)	Own process innovations (developed mainly by own enterprises)
Adaptive ...	
... technology adoption (AdTA)	Innovation mainly by or in co-operation with other enterprises/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 activities
IV. Cumulativeness (CuType)	
Highly cumulative knowledge (High)	Creative entrepreneurs: internal sources more or equally important than external sources; Adaptive entrepreneurs: external sources more important
Low cumulativeness of knowledge (Low)	Creative entrepreneurs: internal sources less important than external sources; Adaptive entrepreneurs: internal sources more or equally important
None	Firms reporting neither internal nor external sources of high importance

Table 3: Distribution of firm types by country group in %

	Continental	North	South	NMS10	NMS2	Total
A. Entrepreneurship (EnType)						
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 / Innovation activity (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 4: Crosstabulation of firm types (shares in %)

	A. Entrepreneurship (EnType)						B. Opportunity (OpType)					C. Appropriability (ApType)						D. Cumulativeness (CuType)
	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 5: The new sectoral taxonomies

Nace	Industry	EnType	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:

EnType – *HCRE*: High creative entrepreneurship with product (and process) innovations; *MCRE*: Intermediate creative entrepreneurship only with process innovations; *TAD*: Adaptive entrepreneurship with technology adoption; *Other*: Adaptive entrepreneurship 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 6: Innovation intensity and labour productivity growth, 1995-2004 (t-value in brackets)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln LPI 1995	-0.0209***	-0.0310***	-0.0052	-0.0153***	-0.0158	-0.0388***	-0.0460***	-0.0433***	-0.0323**
	(-3.58)	*(-5.19)*	*(-0.59)*	*(-1.42)*	*(-1.66)*	*(-6.44)*	*(-5.19)*	*(-2.87)*	*(-2.10)*
Average Capital Income Share	0.0759***	0.1518***	0.0603**	0.1014***	0.1582***	0.1679***	0.1715***	0.1734***	0.1480***
	(5.38)	*(7.57)*	*(2.07)*	*(2.97)*	*(4.44)*	*(8.34)*	*(5.82)*	*(3.65)*	*(3.12)*
Δ Ln Capital Income Share	0.1901***	*0.2198****	0.3427**	0.3406***	0.3316***	0.1265***	0.0877*	0.0977	0.0863
	(5.66)	*(5.51)*	*(4.39)*	*(3.48)*	*(5.04)*	*(3.17)*	*(1.89)*	*(1.28)*	*(1.13)*
Δ Ln ICT Share in Capital Income			0.0529**						
			(2.20)						
Δ Ln High-skill Share in Hours Worked				0.4352*					
				(1.85)					
Ln Firm Turnover (Employment weighted)					0.0095**				
					(2.18)				
Ln Average Firm Size						0.0057***			
						(2.86)			
Ln Average Herfindahl-Hirschman Concentration Index							0.0036*		
							(1.83)		
Ln Export Openness								0.0151*	
								(1.96)	
Ln Import Openness									0.0190**
									(2.36)
Med.-high I (vs. High II)		-0.0435***	-0.0354***	-0.0588***	-0.0143	0.0306***	-0.0331***	-0.0446***	-0.0425***
		(-6.31)	*(-3.56)*	*(-4.97)*	*(-0.94)*	*(-4.16)*	*(-4.36)*	*(-3.67)*	*(-3.49)*
Medium II (vs. High II)		-0.0482***	-0.359***	-0.0617***	-0.0248*	-0.0378***	-0.0445***	-0.0488***	-0.0460***
		(-6.52)	*(-3.28)*	*(-4.73)*	*(-1.81)*	*(-4.99)*	*(-5.66)*	*(-3.26)*	*(-3.06)*
Med.-low II (vs. High II)		-0.0608***	-0.0486***	-0.0725***	-0.0448***	-0.0507***	-0.0541***	0.0571***	-0.0463***
		(-7.81)	*(-4.18)*	*(-5.08)*	*(-2.74)*	*(-6.42)*	*(-6.27)*	*(-3.09)*	*(-2.29)*
Low II (vs. High II)		-0.0463***	-0.0278**	-0.0568***	-0.0252*	-0.0364***	-0.0475***	-0.0633***	-0.0639***
		(-6.06)	*(-2.49)*	*(-4.16)*	*(-1.92)*	*(-4.80)*	*(-4.30)*	*(-3.52)*	*(-3.56)*
Constant	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed Industry Effects	yes	no	no	no	no	no	no	no	no
Fixed Country Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Number of obs.	547	418	134	175	97	242	180	144	143
Adj. R^2	0.40	0.30	0.31	0.24	0.36	0.41	0.43	0.31	0.31

Note: levels of significance *** significant at 1% ** significant at 5%, * significant at 10%.

Source: EU KLEMS, Eurostat SBS, UN Comtrade; WIFO calculations.

Table A.1: The sectoral taxonomy of entrepreneurship types (EnType)

NACE	*Cont/North*	*South*	*NMS10*	*NMS2*	*Consensus*
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 entrepreneurship with product (and process) innovations;
2. = MCRE: Intermediate creative entrepreneurship with process innovations;
3 = TAD: Adaptive entrepreneurship with technology adoption;
4 = Other: Adaptive entrepreneurship pursuing opportunities other than from technological innovation.

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

Nace	***Cont/North***	***South***	***NMS10***	***NMS2***	***Consensus***
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

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

NACE	*Cont/North*	*South*	*NMS10*	*NMS2*	*Consensus*
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

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

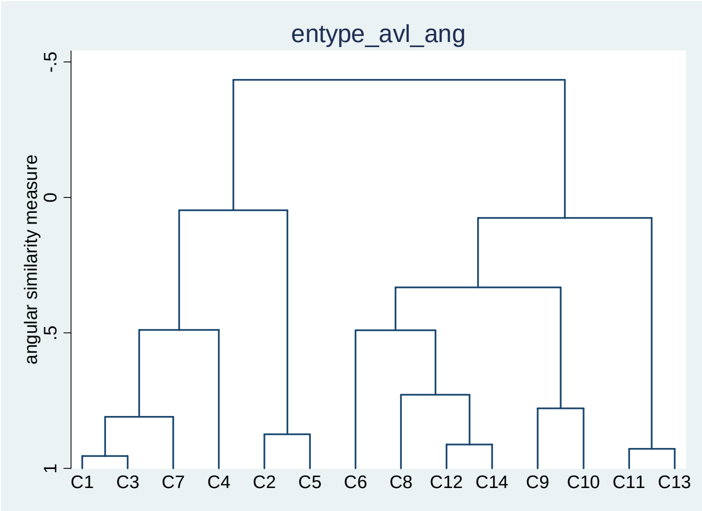
NACE	*Cont/North*	*South*	*NMS10*	*NMS2*	*Consensus*
10	3	3	3	3	**3**
11	2		3	1	**2**
14	3	3	3	3	**3**
15	3	2	1	3	**3**
16	3	3	2	2	**3**
17	1	2	2	2	**2**
18	3	3	3	3	**3**
19	2	3	3	3	**3**
20	2	3	3	3	**3**
21	2	2	2	2	**2**
22	3	2	3	3	**3**
23	2	1	2	1	**2**
24	1	1	1	1	**1**
25	1	1	1	1	**2**
26	2	2	1	2	**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 …

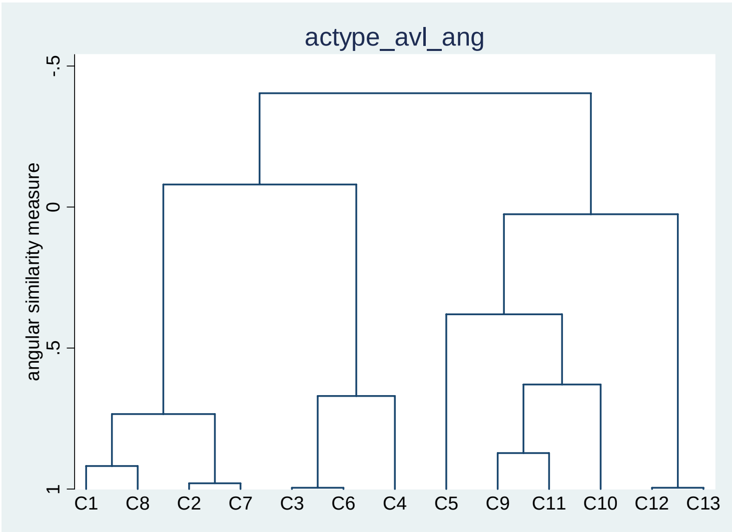
1 = High
2 = Med
3 = Low

Figure 1: Dendrograms for Average Linkage Method and Angular Separation Measure of Similarity

A. Sector types: entrepreneurship (EnType)

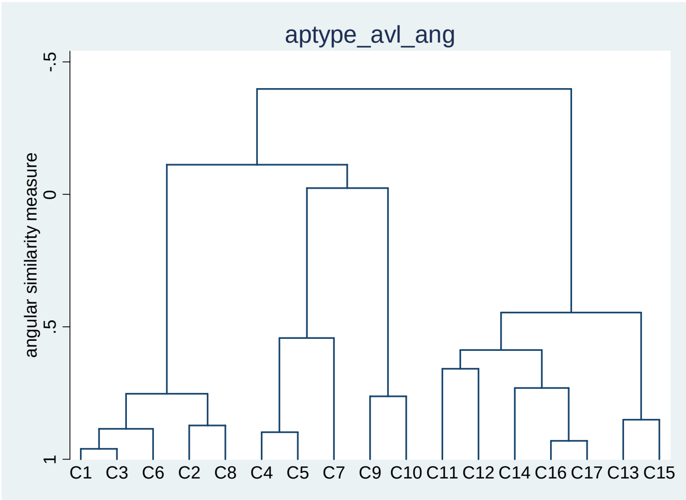


B. Sector types: opportunity conditions (OpType)

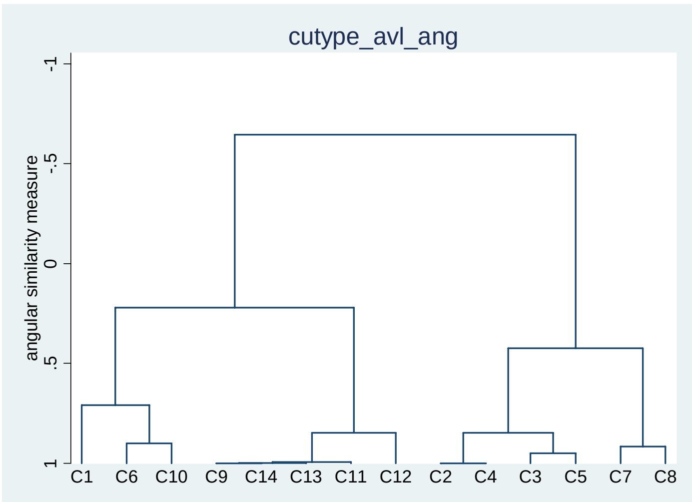


Note: Observations C1 to Cn are the solutions from the *k*-means method in the first stage of the clustering process.

C. Sector types: appropriability conditions (ApType)



D. Sector types: cumulativeness of knowledge (CuType)

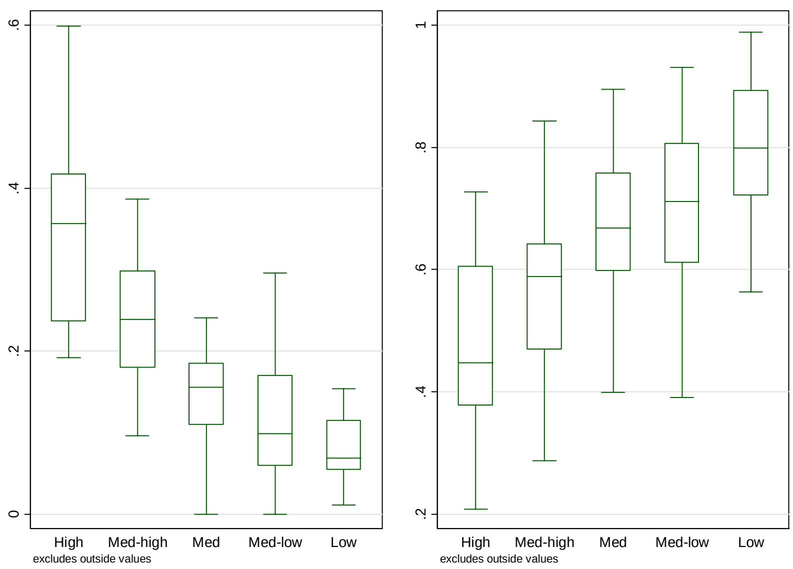


Note: Observations C1 to Cn are the solutions from the *k*-means method in the first stage of the clustering process.

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

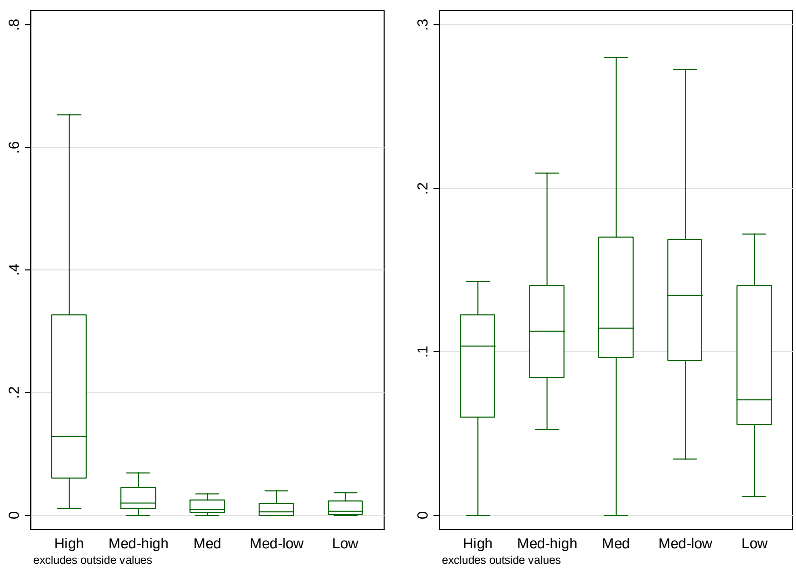
A. Firm types: entrepreneurship (EnType)

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



B. Firm types: opportunity conditions (OpType)

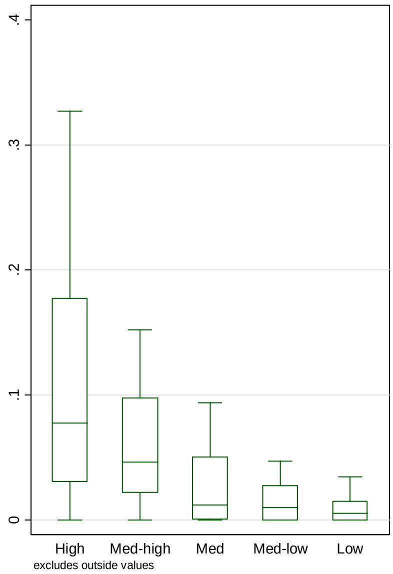
High R&D (HR&D) Acquisition (ACQU)



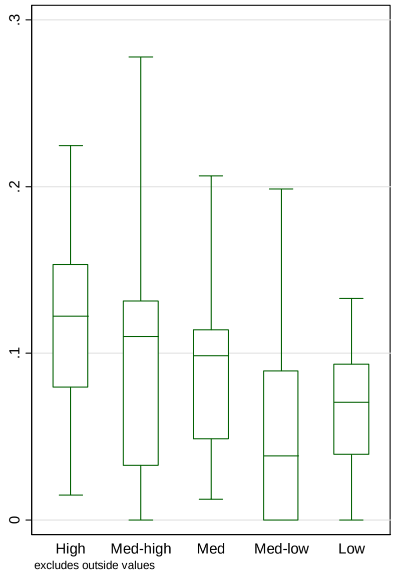
Note: The boxplots display the distribution of the specified firm types by the sector taxonomy of innovation intensity (InnoType) indicated at horizontal axis.

C. Firm types: appropriability conditions (ApType)

Patents (PAT+)

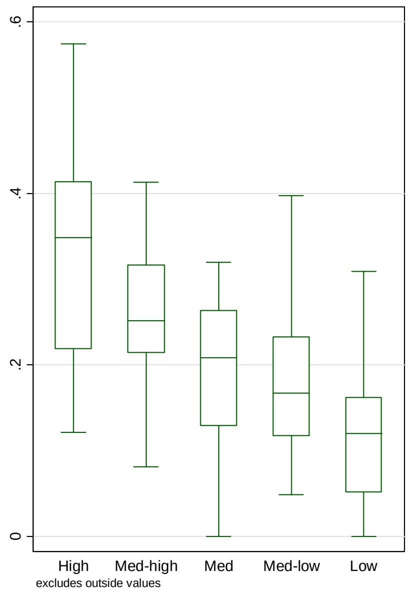


Strategic (STRAT)

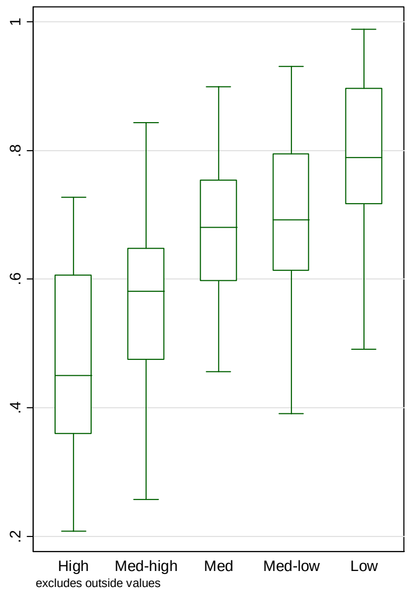


D. Firm types: cumulativeness of knowledge (CuType)

High cumulativeness



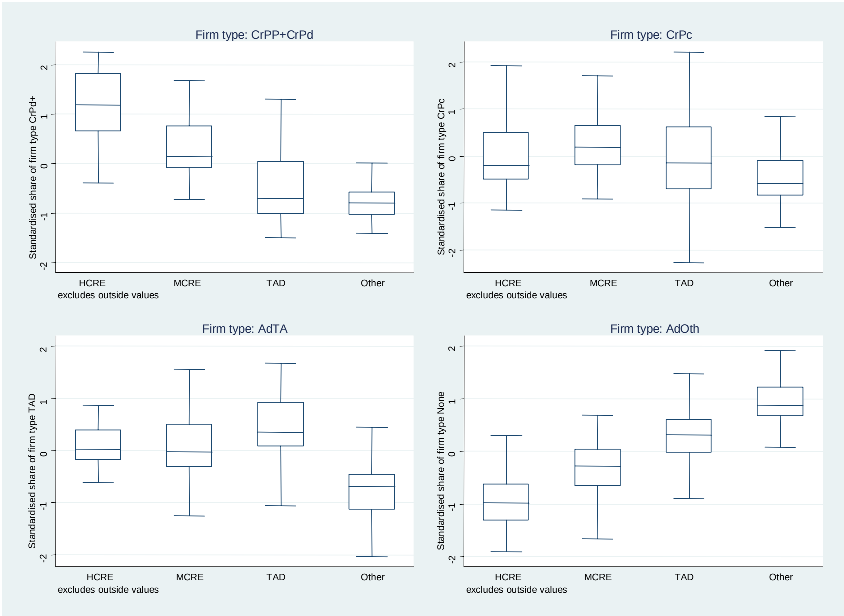
None



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

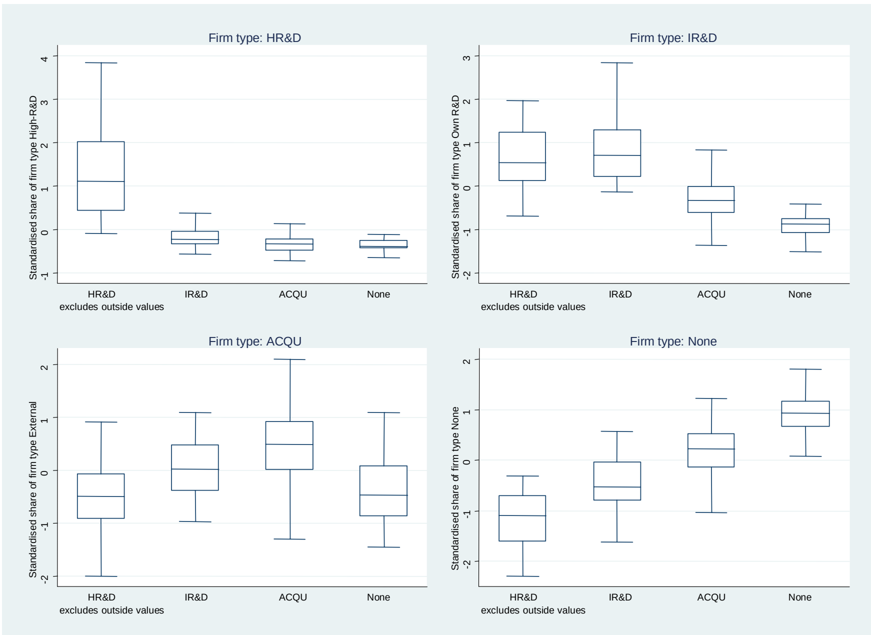
Figure A.1: Distribution of firm types' shares by sector classification

A. Firm and sector types: Entrepreneurship (EnType)



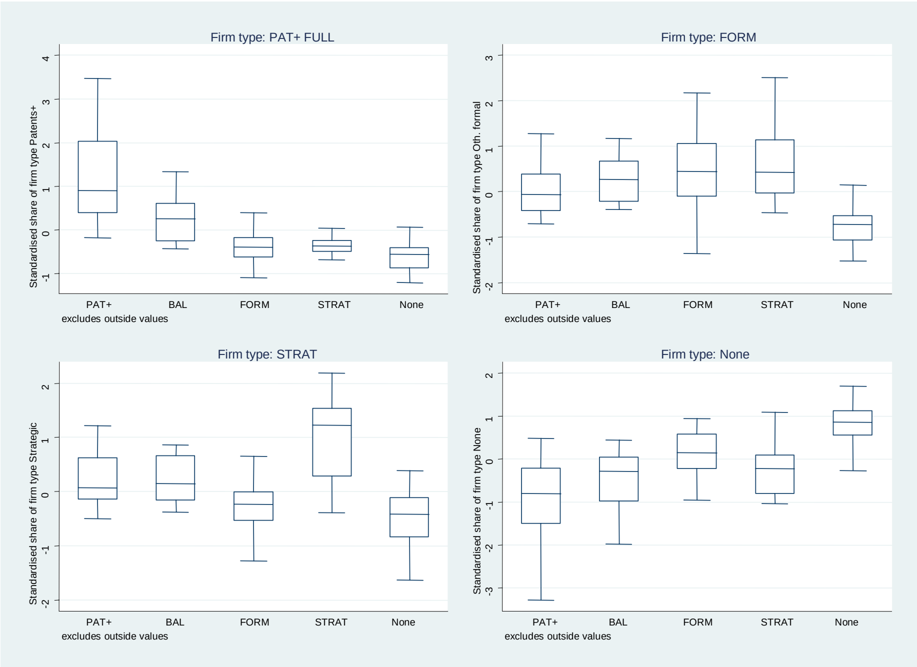
Note: The boxplots display the distribution of the specified firm types by sector types (indicated at horizontal axis).

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



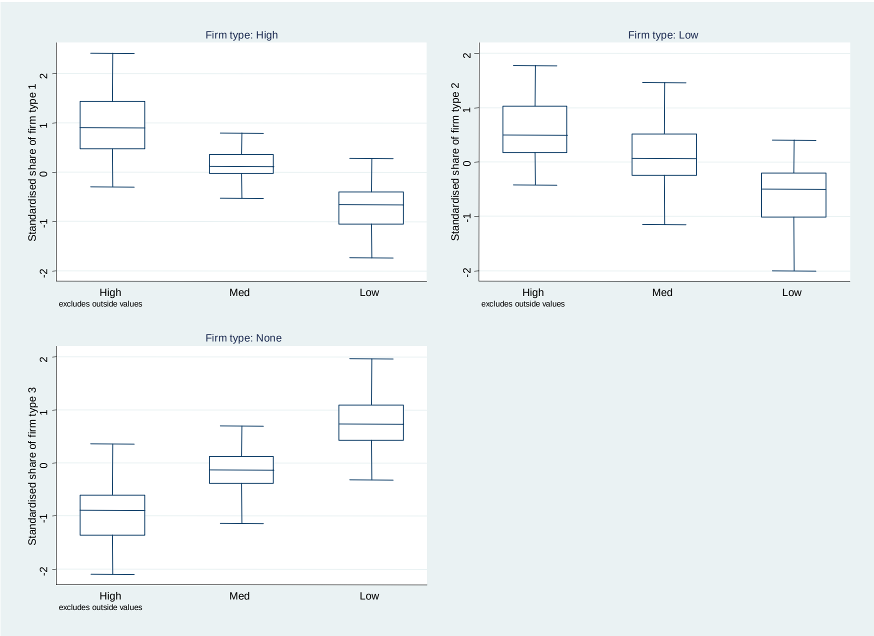
Note: The boxplots display the distribution of the specified firm types by sector types (indicated at horizontal axis).

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



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

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