The Voyage of the Beagle in Innovation Systems Land. Explorations on Sectors, Innovation, Heterogeneity and Selection

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Abstract

The aim of the paper is to assess heterogeneity of the innovation process. Using exploratory factor analysis on micro data from the third Community Innovation Survey in 13 countries, we identify four factors that that can be interpreted as research, user, external and production ingredients of innovation. All too often it is assumed that the differences between the rates at which these factors are found in firms' innovation strategies can be accounted for by differences across sectors and/or countries. To put this proposition under scrutiny, we partition variability of the innovation process into components identified by the different levels. The analysis shows that sectors and countries matter to a certain extent, but far most of the variance is given by heterogeneity among firms within either sectors or countries. On the other hand, a grouping of firms produced by cluster analysis accounts for a much higher share of the variance, which implies that the most relevant contextual factors cut across the established boundaries between sectors and countries. We discuss the implications of these findings for the literature on national and sectoral systems of innovation, and for the way in which evolutionary economics has analyzed the role of selection.

Keywords: Innovation, heterogeneity, sectoral systems of innovation, factor analysis, variance components analysis.

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1. Introduction

One of the most influential views in the economics of innovation is that the sectoral dimension explains a large part of differences in innovative behaviour between firms (e.g., Pavitt, 1984, Malerba and Orsenigo, 1996 for empirical contributions, and Dosi et al., 1995, for a theoretical contribution). The main contribution of this paper is to challenge this common wisdom on the evolutionary grounds that we should take firm heterogeneity very serious, even within sectors and countries (Nelson, 1991). Like Darwin went on his 'Voyage of the Beagle' to collect evidence on the role of heterogeneity in natural history, we will sail out to investigate firm heterogeneity with respect to innovation. We investigate what role sectors (and countries) play in heterogeneity, will also sketch the general theoretical directions to explain heterogeneity in a more complete way than evolutionary economics has so far been able to do.

A notion of "innovation strategy" shall be used in this paper to extend the analysis of innovation beyond the common measures based on either R&D or patents. All too often economists tend to adopt this one-dimensional perspective, as in the literature on the "innovation production function" (Crépon and Duguet, 1998), which puts forward a rather simple input-output relation for innovation. Researchers in the evolutionary economics tradition, following Nelson and Winter (1982), have criticized this approach on the ground that the underlying assumption of perfectly rational behaviour of firms is unrealistic for analysis of the innovation process, and instead propose a model of firm behaviour that is based on routines and heuristics. As we will argue below, this is much in line with the body of theory known as the "resource-based" theory of the firm. Strategic behaviour of firms examined by these theories is therefore the logical starting point of our analysis.

Since the mainstream optimization view of the firm posits that there is only a single solution (e.g. marginal cost pricing in perfect competition), there is not much room for heterogeneity in such a framework. On the other hand, the key element of evolutionary economics is that firms in the "real world" show considerable heterogeneity with regard to the routines and strategies that they apply. This is usually related, among other things, to different skills of their workers, different experiences, and differences in firm size and organization forms (Nelson and Winter, 1982, Nelson, 1991). And the conjecture of heterogeneity in innovative behaviour has been further elaborated in the economic and organizational analysis of innovation (Christensen, 2002, Massini, Lewin and Greve, 2005).

We accept this evolutionary view of firm behaviour as the most realistic representation of the innovation process. At the same time, however, it is our view that the literature has largely ignored one important question, which is how market selection influences the observed level of heterogeneity of firms. The basic point about selection in an evolutionary environment is that it somehow rewards those actors that have adopted strategies that give them a competitive advantage, and punishes those that have chosen strategies that are less competitive. It is a small step from this idea to Metcalfe (1994, p. 330), who states that "selection destroys the measure of variety on which it depends, so that (...) the variance of behaviour is driven to zero by selection". Thus, the force of selection may work against heterogeneity, and it is unclear what level of heterogeneity to expect in the data. In other words, while we accept the point about routines, heuristics and bounded rationality that promote, *ex ante*, differences in innovation strategies, we also ask more explicitly than has been customary in the evolutionary economics literature to what extent selection is able to weed out such heterogeneity *ex post*.

The Community Innovation Survey (CIS) provides the much needed broader view of innovation than the traditional R&D-based framework (Smith, 2004), including different innovation outputs, a range of innovation inputs in addition to R&D, as well as data on sources of information for innovation, cooperation partners and protection of intellectual property. Hence these data allow us to quantify how much innovation efforts a firm makes, but especially what kinds of innovation efforts it makes. For this we adopt the term innovation strategy, and the CIS data provide us with an ideal test bed for exploring the heterogeneity of innovation strategies.

The first aim of the paper is to quantify such innovation strategies based on the available European-wide evidence from the CIS data. We use exploratory factor analysis to classify firms' innovation efforts, and to investigate whether the results of such a classification can be linked to the typologies proposed in the literature. The analysis is based on micro data from the third Community Innovation Survey (CIS-3) provided by Eurostat, which asked firms about various aspects of their innovation activity from 1998 to 2000. This part of our research is complementary to that of, e.g., Arundel et al. (2007), Jensen et al. (2007) and Leiponen and Drejer (2007), who also attempt to identify innovation strategies (or 'modes', or 'regimes') in cross-sectional firm datasets. In comparison to these papers, our dataset covers a larger range of countries, and consequently has much more observations.

Going beyond the scope of these existing "taxonomy" studies, the second research question comes back to the expected level of heterogeneity between firms in the innovation process. Here the task that we set for ourselves is to collect the descriptive evidence on how much heterogeneity remains after both market selection and firm routine behaviour have done their work. In other words, we aim to present a set of stylized facts about heterogeneity that evolutionary innovation scholars may use as input for further theorizing. Although we are unable to provide a dynamic picture of heterogeneity, it is clear from our results that selection has far from weeded out firm-level heterogeneity in innovation strategies in the static sense.

This second research question ties in closely with the work on national and sectoral systems of innovation (Lundvall, 1992; Nelson, 1993; Malerba and Orsenigo, 1995). The main thrust of these literatures has been that diversity in the way how firms innovate can be explained at least partially by differences across sectors and/or countries. At the sectoral level, there is a long tradition, starting with Pavitt (1984), that has attempted to taxonomize sectors in terms of their innovation strategies. Our work, in line with that of Leiponen and Drejer (2007), assesses to what extent such sectoral perspectives are relevant. The analysis shows that sectors and countries matter to a certain extent, but most of the variance is explained by heterogeneity among firms within both sectors and countries.

The question of heterogeneity in firm innovation strategies is extremely relevant both from a theoretical and practical point of view. At the theoretical level, it is a way of sharpening the discussion between the evolutionary and mainstream traditions. From the evolutionary point of view, it provides an insight into the working of selection in different market environments, and addresses the question whether or not the mainstream prediction of homogenous behaviour is observationally equivalent with the outcome of the selection process. From the practical point of view, our results about heterogeneity provide insights with regard to whether a generic technology policy is likely to be effective.

The rest of this paper is organized as follows. In Section 2, we survey the work on heterogeneity that has taken place in evolutionary economics. We also briefly review the relevance of the systems of innovation literature for our work in this section. In Section 3, we present the data that we will use. In Section 4, we present the analysis aimed at identifying innovation strategies. Section 5 looks at the variety of these strategies in the sectoral and national context, and Section 6 presents alternative ways of grouping firms on the basis of their innovation strategies. Finally, Section 7 summarizes the paper, draws conclusions an implications of our results, and discusses future avenues for theoretical and empirical research.

2. Sources of heterogeneity and selection: a theoretical overview

2.1 Routines, heuristics and the theory of the firm

Innovation is considered as a key factor determining the competitiveness of firms, not only by policymakers, but also by economics and management research. While the original work in evolutionary economics by Nelson and Winter (1982) took Penrose (1959), Cyert and March (1963) or Simon (1991) as the starting point for the behavioural basis of their theory, in the light of modern theory of the firm, the so-called resource-based view of the firm (Wernerfelt, 1984) seems to be an adequate synthesis to describe these ideas. The resource-based literature views the important resources that firms use as heterogeneous and non-mobile. The aim of this literature is to explain the competitiveness, or potential for value creation, of firms, often in a comparative (between firms) setting.

Amit and Schoemaker (1993) suggest the term capabilities for describing those resources of the firm that are specific and not easily tradable. These capabilities are the core of a long-run, sustainable ability of the firm to be competitive, and hence of the resource-based theory of the firm. It is the non-mobile, or non-imitable character of these capabilities that makes the competitive advantage that results from it sustainable. Any resource that is easily imitable by other firms will lead to competition, and hence erode value creation. Because knowledge and human capital are prime examples of capabilities that are not easily transferred between firms, innovation is a very natural topic for a resource-based view of the firm (Teece and Pisano, 1994). The economic literature on innovation, with Schumpeter's (1939) idea of entrepreneurship, and Nelson and Winter's (1982) 'evolutionary' view as a central topic, closely links up to this idea (Montgomery, 1995).

Our evolutionary interpretation of the resource-based theory of the firm holds that firms, even when working in a similar selection environment such as a sector or country, may adopt widely differing strategies, because they start from different resource bases, interpret the environment differently, and use different 'models' for reaching decisions on firm strategy. We tie this view more specifically to the innovation literature in economics (Nelson, 1991, Dosi, 1992, Dosi and Marengo, 2007), which argues that firms employ a broad range of possible forms, sources and outcomes of innovation processes. Important dimensions along which this variety of innovation activities has been analyzed include (but are not limited to) knowledge sources (e.g., Laursen and Salter, 2004), cooperation in innovation (Powell et al, 1996), joint ventures (Mowery, 1989), imitative innovation (Cohen and Levinthal, 1989), geographic location of innovation activities (Von Hippel, 1994), and the degree, extent and effects of innovation (Bower and Christensen, 1995). All these issues can be summarized under the question *how* firms innovate, as opposed to the question *how much resources* they devote to innovation.

Jensen et al. (2007) use these ideas to formulate two broad 'modes of innovation': a science, technology and innovation mode, and a doing, using and interacting mode. They find evidence that in a sample of Danish firms, this distinction is relevant, and explore its consequences for innovation patterns. Other work in the area, e.g., Marsili and Verspagen (2002), or Leiponen and Drejer (2007), do not specify the innovation modes *a priori*, but instead use an explorative methodology. This has the advantage of a more open-ended outcome, which is an advantage because we have no particular reason to believe that the large heterogeneity that may be associated with the above considerations, can be harnessed in a two-mode (or three-mode) scheme.

2.2. Selection and heterogeneity

Heterogeneity due to behavioural factors is only one side of the evolutionary coin. Selection is the other one. Selection will reward strategies that are associated to high competitiveness (a notion that we purposely choose not to operationalize beyond the definition given above), and punish strategies that imply low competitiveness. As Nelson (1991, p. 66) put it, "[t]here are winners and losers in Schumpeter's process of 'creative destruction', and these are not determined mainly in ex ante calculations, but largely in ex port actual contest". But in many popular accounts of evolution, simplifying the adage "survival of the fittest", it is argued that, as a result of selection, only limited heterogeneity is left. This is, for example, the main idea in Friedman's (1953) argument that economic evolution leads to the survival of firms that maximize profits only (and hence that the mainstream profit maximizing theory is adequate). However, it is clear, at least from the biological debate, that such a view of selection as unequivocally leading to homogeneity, is false.[1]

Even though we do not intend to accuse the field of having embraced a simplistic view of evolution, it seems to us that evolutionary economics has largely ignored the question how selection impacts on heterogeneity. As a result, we know relatively little about how much heterogeneity to expect after firms bring their innovation strategies to the market. The best we feel we can currently do is to borrow some general ideas from the biological literature on evolution, to confront these with our empirical evidence below, and thus to draw inspiration for future theory development in evolutionary economics.

In biology, there are at least three reasons why considerable heterogeneity may be left even after selection has been working for a considerable amount of time. One is that the exogenous parts of the selection environment are highly variable. To see the impact of environmental variability, it is easiest to imagine a situation where the selection environment is completely stable for a long time. In this case, the evolutionary process may settle in a kind of steady state, were all niches for survival are occupied by highly evolved species. If, on the contrary, the environment is highly variable, a "restless world" (Richerson, Bettinger and Boyd, 2005) may result in which new niches are constantly created. When these are starting to be occupied, heterogeneity in the evolutionary process will increase.

Another reason for heterogeneity from selection is given by the so-called neutral theory of evolution (e.g., Kimura, 1986). This is a theory for biological evolution, and it states that large parts of the genome of organisms do not have any particular influence on fitness of the organism. As a result, these "neutral" parts of the genome are not subject to selection, and heterogeneity can flourish without selection weeding it out. Applying this straightforwardly to the case of economic selection on innovation strategies, it is possible that certain parts of an innovation strategy are "neutral", and hence there is no selective pressure that reduces heterogeneity in this part of the strategy. For example, it might be the case that in certain selection environments, innovations resulting from internal and external R&D result in equally competitive products, and hence we would not expect that selection favours any particular firm in terms of its ratio of internal to external R&D expenditures. The natural way to test for such neutrality of elements of the innovation strategy would be to relate various elements of innovation strategies to firm performance, something that we consider to be interesting for future research, but beyond the scope of this paper.

The idea of neutral evolution is related to that of the so-called complexity catastrophe (Kaufman, 1993). This is the phenomena that in models of evolution on rugged fitness landscapes, the expected fitness of local peaks will decrease with complexity (see Rivkin, 2000, for an application to firm heterogeneity). In less technical terms, this means that when the se-

[1] Essletzbichler and Rigby (2005) also briefly discuss this, and present evidence on heterogeneity in plants productivity that is consistent with our findings below.

lection environment contains many local niches rather than one global one, heterogeneous behaviour tends to be ‘punished’ relatively less by selection. Firms occupy the local niches, and therefore appear as heterogeneous in terms of their behaviour, but this does not lead to large differences in observed fitness.

A final reason for heterogeneity to withstand selection can be found in evolutionary game theory (Maynard-Smith, 1982), and stresses that a mixed strategy (especially so at the population level) may be an evolutionary stable strategy (e.g., Bergstrom and Godfrey-Smith, 1998). An evolutionary stable strategy specifies is a strategy that cannot, at the population level, be successfully invaded by alternative strategies (and hence is a stable outcome of selection). Possibly, evolutionary stable strategies are mixed strategies, e.g., a situation in which a part of the population plays one strategy, and another part plays a different strategy. Hence, behavioural heterogeneity plays a large role in evolutionary game theory.

The well-known game of Doves and Hawks is an example of such a mixed strategy outcome. In this game, a player can adopt either an aggressive strategy (Hawk) or a passive strategy (Dove) in a fight for some resource (e.g., food). When Hawks meet, a fight takes place in which both players are damaged, i.e., their pay-off is low. When a Dove meets a Hawk, the Hawk takes the complete pay-off, and when Doves meet Doves, they share (with an intermediate pay-off for both). Each round of the game consists of a random match of two individuals, which implies that the probability for meeting a Dove or a Hawk is equal to their sampling frequencies. The point of the example is that in a population of either only Doves or only Hawks, the entry of the other strategy would be evolutionary stable. Starting with only Doves, the first Hawk to enter could obviously survive, since it will always ‘win’. But with only Hawks, two Doves entering would also survive, since they would share the resource on the (rare) occasion that they meet, and then have a higher pay-off than the Hawk-Hawk meeting. Obviously, the evolutionary stable strategy is somewhere in the middle, with a mixed population of Doves and Hawks. Metaphorically, we can imagine that, for example, a mixed strategy outcome of offensive and defensive innovators is an evolutionary stable strategy, and this would lead to observed heterogeneity of innovation strategies within a single selection environment.

None of these three reasons for finding substantial heterogeneity after economic selection has taken place are full-fledged theories of innovation, selection and heterogeneity. But we view them as interesting ways forward for future theory development, and as motivating reasons to explore the issue of innovation strategies from an evolutionary point of view.

2.3 Sectoral and national innovation systems

Before we proceed to explore innovation strategies and their heterogeneity among firms, we briefly survey a literature that has approached this issue from a different, less explicitly evolutionary, corner. This is the literature on national and sectoral systems of innovation. Our interpretation of this literature is that in its core, it argues that the most important part of the heterogeneity of innovation strategies is between rather than within such systems. But at the same time, it must be observed that there is a striking lack of attention to quantifying the within-sector or within-country dimension of firm heterogeneity, relative to between-sector or between-country differences. In the words of Nelson (1991, p. 61), “[i]n virtually all economic analyses, differences between firms in the same line of business are repressed”.

In the sectoral literature, a tradition has emerged to taxonomize sectors and the firms within them into larger groups, each of which has a typical innovation strategy. This is the central idea in Pavitt (1984), and much of the work that follows it (e.g., Malerba and Orsenigo, 1995, 1996, Marsili, 2001, for surveys see Archibugi, 2001, Peneder, 2003). This idea of a sectoral taxonomy of innovation can be seen as a way to reduce heterogeneity into a limited number of stylized patterns, and these stylized patterns have a close relation to economic sectors.

In the sectoral view, the starting point for such a way of reducing heterogeneity has been the idea that the nature of the innovation process depends on the context within which it occurs. Pavitt (1984) compared sectors according to sources of technology used in the innovation process, nature of the technology produced, sectors of use of their innovations, and characteristics of innovating firms with regards to their size and principal activity. Using information on these variables for 2,000 significant innovations in British firms over 1945-1979, he identified common technological patterns at the sectoral level, and categorized the various manufacturing industries into four groups: 1) Supplier-dominated, 2) Scale intensive, 3) Specialized suppliers, and 4) Science-based sectors. It should be pointed out, however, that what Pavitt really had in mind when constructing the taxonomy was how the innovation process is organized within firms (and what the differences in this respect between firms are). Nothing can be more revealing than this quote from the original paper: "…technology trajectories are directions of technical development that are cumulative and self-generating, without repeated reference to the economic environment external to the firm." (Pavitt, 1984, p. 355).

Using our own evolutionary perspective of the previous sub section, we observe that even if the sector clearly delineates a specific selection environment, i.e., if sectoral specificities of the knowledge base as identified by Pavitt and others are indeed main determinants of selection, there is no reason to unequivocally expect that this leads to low within-sector heterogeneity of firms. We identified three reasons, all drawn from general evolutionary theory, that may lead to a state of play in which there is considerable heterogeneity between firms even within a clearly delineated selection environment. Hence, it is our contention that even if sectors are clearly different in terms of their knowledge bases, they may or may not have a mixture of innovation strategies among their firms. We will therefore set out, in the balance of this paper, to assess within-sector heterogeneity of innovation strategies on an equal footing with between-sector heterogeneity.

In the two-step process that Pavitt adopted (aggregation of the firm-level data to the sectoral level, and subsequently reducing this to identify the four sectoral classes), a lot of firm-level diversity may have been lost. The literature following Pavitt, until Leiponen and Drejer (2007), has not returned to the question how firm level heterogeneity within the sectors, let alone the sectoral aggregates, related to that between the sectors and the four classes of the taxonomy. Instead, the literature has used the taxonomy as a useful classification tool in empirical work that does away with the strongest effects of heterogeneity. Our proposal in this paper is to go back to the lowest level of heterogeneity, i.e., the firm, and formally address the question how aggregation affects the loss of this heterogeneity.

Although Leiponen and Drejer (2007) take the idea of within-sector heterogeneity in innovation strategies very serious, their analysis is limited in many accounts. For example, they are somewhat arbitrary in choosing variables for identification of innovation strategies, and there may be methodological problems in the way they apply factor analysis (we will return to this in Section 4). Most importantly, they provide only simple descriptive evidence based on frequency tables on how much sectors matters in explaining innovation strategies, and apply no statistical testing of this issue. Therefore, while we fully acknowledge the importance of Leiponen and Drejer (2007) in drawing our attention to within-sectoral heterogeneity, we extend their analysis in several ways.

Sectoral and firm level patterns of innovation are also determined by local institutional, cultural and other factors, which is well-understood in the literature on national innovation systems (Lundvall, 1992; Nelson, 1993). The idea in this literature, similar to that in the sectoral literature, is that heterogeneity between firms is somehow smaller within national borders than it is between countries. Much the same critique about ignoring heterogeneity within national systems applies to this literature, although we acknowledge that the national systems literature has been less forthcoming in terms of quantitative analysis of heterogeneity.

Moreover, sectoral and national systems of innovation interact. In particular, sectoral patterns of innovation in small, structurally different and, most importantly, developing countries differ substantially from their general characteristics observed in the rest of the world. It is too often taken for granted in the empirical literature that the taxonomic characteristics of industries are equally relevant across countries (and in time), and the taxonomy is applied in a "one-fits-all" manner in empirical research (Srholec, 2007). The identification problem is not resolved by grouping industries once for all (Peneder, 2003). Since countries differ in their institutions, culture (etc.), also sectoral technology trajectories differ even if the principal activity of firms appears to be the same according to standard industrial classifications.

Each system, however, needs to be defined by some boundaries (Edquist 1997). An essential issue in the literature on innovation systems, which remains largely unresolved (at least empirically), is how these systems should be delineated. What is the most relevant context that shapes innovation strategies of firms? At which level of the analysis do the forces towards similarity in the innovation process work? In the light of input-output relations, it might well be the case that the answer to these questions is that the best level of aggregation runs across sectors and countries, i.e., systems of innovation combine subparts of different industries and countries. In our analysis, we will compare the outcomes of an analysis based on delineation of systems based on industry- and country dummies, with one based on a more open-ended approach in which systems may cross these boundaries.

We conclude that there are not many studies that directly investigate and test the relevance of the sectoral and national patterns by quantitative analysis that also takes into account firm-level heterogeneity. One of the reasons used to be a lack of disaggregated data on innovation, but the CIS databases, which are now commonly available at the micro level in most countries in Europe and some countries in the rest of the world, seem to fill this gap. How much of the innovation strategy of the firm is determined by the sectoral or national context, or by a notion of innovation system that runs across these two dimensions, and how much is given by heterogeneity at the firm level? In order to answer this question, we fist need to identify the variety of innovation strategies that can be observed at the firm-level.

3. Overview of the dataset

The analysis is based on micro data from the third Community Innovation Survey (CIS-3) provided by Eurostat (Eurostat, 2007), which asked firms about various aspects of their innovation activity from 1998 to 2000 (or in some countries from 1999 to 2001).[2] Following the Oslo Manual (OECD, 1997), a harmonized questionnaire and methodology was used to collect the data. Since our focus is on heterogeneity of innovators, only firms that successfully introduced product or process innovation over the period are included in the analysis. After omitting observations with incomplete records the survey provides a dataset of 13,035 innovating firms in industry and most sectors of market services (10-74 codes according to NACE, rev. 1.1) in thirteen European countries[3] (numbers between brackets indicate number of observations in our final sample): Belgium (705), Bulgaria (724), Czech Republic (943), Estonia (650), Germany (1,525), Greece (349), Latvia (404), Lithuania (604), Norway (1,355), Portugal (729), Romania (1,736), Slovakia (354) and Spain (2,957).

Information about the innovators in the survey refers to resources devoted to variety of innovation activities, the effects of innovation, the sources of information for innovation, co-operation agreements on innovation, use of methods to protect innovations and to other (non-technological) important changes in the enterprise (for more details on definitions than we provide below, and questionnaires, see OECD, 1997 and Eurostat, 2007).

The first set of variables refers to dummies with value 1 if the firm indicated to engage in a particular activity, as follows: i) Intramural research and experimental development (R&D), ii) Acquisition of extramural R&D, iii) Acquisition of machinery and equipment specifically purchased to implement an innovation, iv) Acquisition of other external knowledge (licenses, software and other), v) Internal or external training directly aimed at implementation of an innovation, vi) Internal or external marketing activities directly aimed at the market introduction of new products, and vii) Design and other preparations for production or deliveries not covered elsewhere. To keep the entire analysis at the firm level, we refrain from using information on innovative expenditures devoted to these activities, because these variables have been micro-aggregated.

A next set of questions asked firms how they benefited from results of the innovative activity. Firms were asked to indicate the degree of the following effects on a four-point scale: i) Increased range of goods or services, ii) Increased markets or market share, iii) Improved quality in goods or services, iv) Improved production flexibility, v) Increased production capacity, vi) Reduced labour costs per produced unit, vii) Reduced materials and energy per produced unit, viii) Improved environmental impact or health and safety aspects, and ix) Met regulations or standards. Answers were coded by integers from zero for "not relevant" to four for "high degree of impact".

As for the sources of information, firms were asked to indicate on a similar four-point Likert scale importance of the following sources: i) Within the enterprise, ii) Other enterprises within the enterprise group, iii) Suppliers of equipment, materials, components or software, iv) Clients or customers, v) Competitors and other enterprises from the same industry, vi) Universities or other higher education institutes, vii) Government or private non-profit re-

[2] Some of the variables in the dataset containing sensitive financial information were so-called micro-aggregated by averaging data for three similar firms. The dummy and Likert scale variables were not transformed, which implies that we only use true micro-data in our analysis.

[3] Data from Iceland and Hungary were excluded from the analysis. Only about one third of innovating firms answered detailed questions on their innovation activity in Iceland. Observations from Hungary were omitted due to missing information on the complexity of design as the method of protection, a very low number of innovating firms in the national dataset and because the small set of Hungarian firms proved to be a major outlier if included in the analysis.

search institutes, viii) Professional conferences, meetings, journals, and ix) Fairs and exhibitions. Unfortunately we can not use the question on the "other enterprises in the group" because this information is not available for the Greek firms. Again the answers were coded by integers from zero for "not used" to four for "high importance".

Somewhat related information comes out from the set of questions on cooperative arrangements on innovation. Innovation cooperation is defined in the survey as active participation in joint R&D and other innovation projects with other organisations. Firms were asked to report whether they had cooperative agreements broken down by a similar division of partners as in the question on sources of information above. Unlike Leiponen and Drejer (2007), we do not use details on cooperation with the different types of partners in the innovation process, because this insight is already captured in the previous set of questions. Since including redundant information in a factor analysis tends to produce "inflated" factors, this clearly needs to be avoided, and therefore we use only the basic information on whether the firm cooperated or not. From this follows that the variable on innovation cooperation is a dummy with value 1 if the firm has any cooperation arrangements (regardless of the partner organization).

Another salient aspect of the innovation process is how the firm protects outcomes of the innovation activity. Firms were asked to indicate whether they used any of the following methods to protect inventions or innovations developed by the enterprise: i) application for a patent, ii) registration of design patterns, iii) Trademarks, iv) Copyright, v) Secrecy, vi) Complexity of design, and vii) Lead-time advantage on competitors. A dummy variable for each option has value 1 if the firm reported to use the respective method of protection.

Finally, a set of dummies with value 1 for a positive answer have been derived from the question on other important changes in the firm, which include i) Implementation of new or significantly changed corporate strategies, ii) Implementation of advanced management techniques within the enterprise, iii) Implementation of new or significantly changed organizational structures, iv) Changing significantly the firm's marketing concepts/strategies, and v) Significant changes in the aesthetic appearance, design or other subjective changes of the product.[4]

Since coverage and response rate of the surveys differ between countries[5], the observations are weighted in the analysis to obtain unbiased results. Size and industry distribution of these observations also differ from the target population. So we weight each observation by the inverse of the so-called sampling fraction, corrected for non-response and for no longer existing enterprises. In practice it means that we give higher weights to firms from underrepresented size categories, industries and countries. Only analysis that takes into account these weights provides representative results, which is an imperative for datasets with data for many countries.

[4] A basic clearing of the dataset has been conducted in the particular order as follows (note that this refers only to the sub-sample of innovating firms). First, we have replaced missing data by zeros if there was at least one valid answer within the particular set of questions (such as the set of questions on the effects of innovation, etc.). Although this may seem as a relative heroic assumption, for some countries this has been apparently done already before distributing the dataset by Eurostat, while for others not, so that this procedure was necessary to harmonize the data along these lines. Second, 528 firms with missing information on any of the variables used in the analysis (after imputation of the missing data by the preceding procedure) were omitted. Third, 1,580 firms with only zeros within each set of questions on the various innovation activities, the effects of innovation or the sources of information were deleted. The reason for this is that every innovating firm must by principle engage in some innovation activity, benefit from some effects and use at least some source of information. All zeros within a set of these questions is therefore likely to reflect unwillingness of the firm to provide the information rather than reporting "no occurrence", "not relevant" or "not used". However, not every innovative firm must necessarily use the methods of protection or implement any of the other changes in the enterprise, so that these sets of question need not to be cleared by this procedure.

[5] For example, there are about 10,000 firms from Bulgaria but only 3,000 firms from Germany in the entire dataset.

4. Identifying innovation strategies

The innovation strategy of a firm is a multidimensional phenomenon. Many typologies of the innovation process have been proposed along the various dimensions and a number of measures have been used to pinpoint their most salient features. How should we resolve empirically what are the relevant dimensions of the innovation process? An obvious possibility is to gather the relevant indicators and attempt to connect the dots by some sort of a descriptive analysis. Such an approach is feasible if a small number of variables suffices for the research purposes. Since the number of dots that need to be connected tends to grow exponentially with the increasing number of variables, however, descriptive attempts to make sense from somewhat richer evidence suffer from severe limits. And we need to take into account a large number of variables in order to derive robust evidence on the different facets of the innovation process.

Fortunately, there is a well developed method of multivariate analysis - the so-called factor analysis – that can help us to identify the underlying structure of the data in a concise manner. Factor analysis has been widely used in psychology and other social sciences for a long time (Spearman, 1904; Hotelling, 1933), but it has been sparsely and only recently used in research on innovation (Hollenstein, 2003; Fagerberg and Srholec, 2006; Fagerberg et al. 2007; Leiponen, Drejer 2007). It is the ideal tool of analysis if data are complex and we are not sure what the most important dimensions are. Unlike Leiponen, Drejer (2007), however, we do not arbitrarily select variables for the analysis, but employ every piece of relevant evidence to let the data decide what are the essential ingredients of the innovation process.

Although it can not be the purpose of this paper to provide a general overview of factor analysis (for more details see Basilevsky, 1994), we need to explain the hierarchical nature of our procedure. First we conduct the factor analysis separately on each set of the CIS questions. Then, in the second-stage, we use factor analysis on factor scores generated by the first-stage estimates. We interpret the results from this second stage as the ultimate dimensions of innovation strategies. The alternative strategy of using factor analysis on all of the variables at once would imply that we allow a firm to have innovation strategy based on frequent use of many different sources of information, but without any decision on activities that needs to be performed in the process (just to give an example how this would clearly not be a realistic representation of the reality).

Even if in practice, decision-making about innovation strategies may not always follow such a hierarchical procedure, and even though the categories in our questionnaire may not be ideal, we prefer this representation because it ensures that all dimensions of the innovation strategy are well represented in our final results. In a metaphor to dressing up comfortably for bad weather, we make sure that we don't go into the cold with five different hats, but put no pants on.

Since the dataset includes binary and Likert scale variables, we use tetrachoric and polychoric correlations in the factoring procedure (Kolenikov, Angeles 2004). The extraction method is principal-component factors.[6] . Before the results are interpreted, it is necessary to rotate the solution. For this purpose we use the oblique oblimin rotation.[7] Only principal fac-

[6] Maximum likelihood factoring requires multivariate normality of the data, which is clearly not a viable assumption for a dataset consisting of binary and Likert scale variables. A major advantage of principal-components factoring is that this extraction method is not based on any distributional assumptions.

[7] Orthogonal rotations, such as the most widely used varimax normalized rotation, are constrained to produce factor scores that are uncorrelated. More complex and recently developed oblique rotations do not impose this

tors with eigenvalue larger than one were retained for rotation, which ensures that the last retained factor explains a higher proportion of the total variance than an "average" variable. Solutions based on this criterion proved to be consistent with the scree test

Tables 1 to 5 provide the overview of the first stage estimates. So-called factor loadings are reported in the tables, sometimes also called the pattern matrix. A factor loading is a coefficient of correlation between a principal factor identified by the estimate (columns) and the original variable (rows). If we flip the coin, the loading indicates the proportion of variance of the original variable that is accounted for by the principal factor.

Table 1 gives results of factor analysis on different innovation activities performed by firms. We have detected three principal factors. The first factor labelled "R&D" loads highly on both internal R&D and acquisition of R&D from external sources, which confirms their complementary role in the innovation process rather than "make or buy" decisions of firms along these lines (Veugelers, 1997; Veugelers and Cassiman, 1999). Also acquisition of other external knowledge seems to complement these R&D inputs to some extent. The second principal factor that has been detected correlates with training, but even more with market introduction of innovations and resources devoted to design and other preparations, so that this aspect has been labelled "Marketing". And the third dimension in the data integrates acquisition of technology embodied in capital goods and the purchase of other external knowledge. We label this principal factor "External". What this summarizes is, on the one hand, a straightforward distinction between R&D-centred and other innovation activities, and on the other hand a difference between innovation based on internal capabilities, and dominated by external inputs.

Table 1: Factor analysis on variety of innovation activities

	(1) R&D	(2) Marketing	(3) External
Internal R&D	0.79	0.11	-0.25
Acquisition of extramural R&D	0.85	-0.03	0.18
Acquisition of machinery and equipment	-0.21	0.05	0.80
Acquisition of other external knowledge	0.32	-0.01	0.71
Training	0.05	0.77	0.28
Market introduction of innovations	0.03	0.91	-0.08
Design and other	-0.04	0.91	-0.06

Note: Estimation weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327); three factors with eigenvalue > 1 were detected, which explain 73.8% of total variance; extraction method: principal components factors; rotation): oblimin oblique.

Table 2 reports results of the factoring procedure on the effects of innovation. A clear distinction between three groups of "Product", "Process" and "Social (corporate) responsibility" effects has been identified. Although many firms introduce product and process innovations simultaneously, not all of them do, and even if firms venture into both types of innovations, they do not tend to benefit from them to the same extent. Since this distinction already comes out from the effects, we do not use separate dummies for the occurrence of product and

restriction. Since the assumption of orthogonality often leads to biased results, we use the more flexible oblique oblimin rotation.

process innovations to avoid redundancy in definition of the variables, which can substantially bias results of the factor analysis. Another distinct dimension in the effects of innovation refers to meeting demands on environmental, health and safety aspects of the business and/or meeting regulations or standards required by the authorities. Awareness of firms of these concerns, which become increasingly integrated into strategy (or at least public relations) of many firms, has been studied under the rubric of "social corporate responsibility" (Carrol, 1999), so that this literature naturally provides a framework for interpretation of the third principal factor.

Table 2: Factor analysis on effects of innovation

	(1) Product	(2) Process	(3) Social responsibility
Increased range of goods or services	0.90	-0.05	-0.04
Increased market or market share	0.87	0.03	-0.01
Improved quality in goods or services	0.56	0.17	0.22
Improved production flexibility	0.07	0.86	-0.07
Increased production capacity	0.00	0.90	-0.03
Reduced labour costs per produced unit	-0.05	0.90	0.00
Reduced materials per produced unit	0.00	0.70	0.25
Environmental, health and safety aspects	-0.05	0.07	0.89
Met regulations or standards	0.05	-0.06	0.93

Note: Estimation weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327); three factors with eigenvalue > 1 were detected, which explain 74.8% of total variance; extraction method: principal components factors; rotation): oblimin oblique.

Table 3 looks at relations between the various sources of information for innovation. There is a separate principal factor for "Science", which puts together information from the university sector and from research institutes. Also this factor loads modestly to information from professional conferences, meetings and journals, which is reassuring, because these are often the devices though which firms communicate with academics and researchers. The second principal factor combines inspiration from clients or competitors on one hand, and from competitors and other firms in the same industry on the other hand, with elements of information from inside of the enterprise. All of these sources are in the business domain, and capture the flows of information horizontally and downstream the value chain, so that we label this dimension "Clients and industry". And the third factor is given primarily by using information from suppliers and from fairs, exhibitions and the other professional sources, which leads to the "Suppliers and events" label. The main finding here is the distinction between information from science and the importance of user-producer interaction with other firms along the value chain (Lundvall, 1988), although the horizontal sources and events tend to somewhat complicate the picture.

Table 3: Factor analysis on sources of information for innovation

	(1) Science	(3) Clients and industry	(2) Suppliers and events
Within the enterprise	0.10	0.54	-0.18
Suppliers	-0.18	0.02	0.68
Clients or customers	0.02	0.87	-0.07
Competitors or firms in the same industry	-0.04	0.72	0.22
Universities and other higher education	0.90	0.04	-0.01
Government or non-profit research institutes	0.91	-0.01	0.00
Professional conferences, journals, etc.	0.42	0.01	0.56
Fairs and exhibitions	0.05	0.03	0.82

Note: Estimation weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327); three factors with eigenvalue > 1 were detected, which explain 63.6% of total variance; extraction method: principal components factors; rotation): oblimin oblique.

Table 4 shows result for the methods of protection. Only two principal factors came out, which conform to the broad distinction between formal and informal strategies. The first factor on the "Formal" methods loads primarily on patents, design patterns and trademarks, while the second factor on the "Informal" methods correlates most to secrecy, complexity of design and the lead-time advantages. Some overlap has been detected in the use of copyrights, which appears to be somewhat half way between the formal and informal categories.

Table 4: Factor analysis on methods of protection

	(1) Formal	(2) Informal
Patents	0.83	0.01
Design patterns	0.91	-0.04
Trademarks	0.76	0.07
Copyright	0.32	0.48
Secrecy	0.02	0.90
Complexity of design	-0.11	0.96
Lead-time advantage on competitors	0.09	0.89

Note: Estimation weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327); two factors with eigenvalue > 1 were detected, which explain 73.3% of total variance; extraction method: principal components factors; rotation): oblimin oblique.

The last estimate in the first stage of the factor analysis refers to the other important changes that occurred in the firm along introduction of the technological innovation. Table 5 reveals that all of these changes tend to be highly correlated to each other and collapse into a single principal factor. Only the aesthetic (or other subjective) changes seems to be a bit different, however not enough to forge a separate factor in the estimate. We shall refer to this factor as the measure of “Non-technological innovation” in the following.

Table 5: Factor analysis on other important changes in the firm

	(1) Non-technological innovation
Strategy	0.82
Management	0.81
Organisation	0.82
Marketing	0.76
Aesthetic (or other subjective) changes	0.52

Note: Estimation weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327); one factor with eigenvalue > 1 was detected, which explains 56.9% of total variance; extraction method: principal components factors; rotation): oblimin oblique.

As anticipated above, in the next step we run a higher-order factor analysis on factor scores for the latent variables that have been derived from the lower-order estimates. We also include the dummy on innovation cooperation, which is meant to complement the picture. Table 6 gives the results. Four distinct ingredients of innovation strategies (i.e., principal factors) are identified as follows:

1) The “Research” ingredient puts together strong R&D capabilities, extensive use of information from science, and a tendency to participate in joint innovation projects with other organizations. Moreover, firms on this path to innovation tend to protect their knowledge base by a combination of both formal and informal methods, which shows that protection of intellectual property rights is a great concern for them. Needless to say, this ingredient represents the often prevalent research-based idea about innovation (and Jensen et al. STI mode).

2) The “User” ingredient is geared toward product effects, involves innovation activities aimed at improving design and a smooth introduction of new products on the market, and requires sensitivity to signals from clients, consumers and firms in the same industry. Somewhat surprisingly this is the ingredient that tends to be most often accompanied by the non-technological changes in the enterprise, such as implementation of new corporate strategy, organization structure or marketing, which indicates that pursing this path to innovation triggers the most profound changes in running of the enterprise. Also various protection methods are used frequently by these firms.

3) The “External” ingredient exploits opportunities for innovation from diffusion of technology embodied in new capital goods and acquisition of existing technology from other organizations by purchase of rights to use patents, licenses or software. Another important element is high importance given to the various sources of information, of which most are external to the firm, with the highest emphasize on suppliers and events. Unlike the former two cases, methods of protection do not seem to be used frequently, which is reassuring, because most of

knowledge used in this ingredient is likely to be either tacit or already available for purchase on the market for technology from other organizations.

4) The "Production" ingredient combines orientation on the process effects of innovation together with a need to live up to the demands on social responsibility of the firm, which, indeed, is by-and-large determined by process technology. Similar to the previous case, firms leaning in this direction do not tend to use any methods of protection extensively.

Table 6: Hierarchical factor analysis (2nd stage) on ingredients of innovation strategies

	(1) Research	(2) User	(3) External	(4) Production
R&D	0.70	0.07	-0.16	0.09
Marketing	0.07	0.65	0.01	-0.16
External inputs	0.16	-0.13	0.65	0.02
Product effects	-0.01	0.69	-0.03	0.15
Process effects	-0.08	0.06	0.02	0.81
Social responsibility	0.08	-0.07	0.01	0.83
Information from science	0.62	0.01	0.31	0.06
Information from clients and industry	-0.01	0.61	0.28	-0.07
Information from suppliers and events	-0.07	0.23	0.69	0.10
Formal protection	0.36	0.37	-0.27	0.05
Informal protection	0.42	0.35	-0.18	0.01
Non-technological innovation	0.00	0.53	0.02	0.12
Innovation co-operation	0.78	-0.06	0.06	-0.09

Note: Estimation weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327); four factors with eigenvalue > 1 were detected, which explain 50.7% of total variance; extraction method: principal components factors; rotation): oblimin oblique.

In calculations that we leave undocumented but which are available on request, we discovered that the majority of firms in our sample do not score high only a single of these four factors. In other words, we do not have many firms that score high on, e.g., the Research factor, and low on the three other factors. This means that the four factors cannot be seen as innovation strategies proper, at least if we adhere to the idea that at any point in time a firm only applies one strategy. At best, we can view the four factors as ingredients of innovation strategies, and we investigate in Section 6 below which combinations of ingredients are particularly frequent, i.e., how innovation strategies combine the four ingredients.

One main conclusion from this seems to be that the strong emphasis on R&D, both by policymakers and scholars, is gravely oversimplifying the matter. All too often innovation policy that neglects the diversity of paths toward successful innovation slips into myopic strategies such as the goals on achieving quantitative targets of R&D spending and alike. Such a framework for thinking about innovation is likely to overlook the essence of the innovation process in many firms, i.e., those that depends mainly on the last 3 of the 4 innovation strategy ingredients that we identify. Innovation policies designed along these lines also hinder evolution of innovation capabilities that are not of purely technical nature such as those based on user-producer interaction, continuing learning, organizational know-how.

5. How much do differences across industries and countries explain?

The large number of variables on various aspects of the innovation process that we employed, can be boiled down into four basic dimensions. It has been advocated by many over the years, as has been discussed above, that patterns of innovation are strongly related to industry, country and other contextual factors. Although Leiponen and Drejer (2007) pointed to the problem of projecting the standard industrial classification on organization of innovation activities, their analysis is inconclusive on how much exactly remains unexplained after taking into account the sectoral patterns. Just how much about innovation is associated to idiosyncratic characteristics of firms? And how much closely do the various ingredients of the innovation process fit into the sectoral and national uniforms?

The method of Variance Components Analysis is designed to advice on questions like these. The aim of the decomposition procedure is to estimate a contribution of a random effect (or a set of random effects) to the variance of a dependent variable. In other words, we are not concerned with making any inferences about causal relations; the only purpose is to partition variance of the dependent variable between different levels at which it can be measured.

We use a variance components model, also called a mixed (or random) effects model, hierarchical model or multilevel model, where the firm represents the first level of the analysis, and is nested in industries and countries at the higher levels. A basic variance components model with this hierarchical structure can be delineated as follows:

(1) $y_{ijk} = \gamma + u_j + v_k + r_{ijk}$

where y is the dependent variable, *i* is the firm, *j* is the industry, *k* is the country, γ is the intercept (the grand mean), u_j is variability between industries, v_k is variability between countries and r_{ijk} is variability of the dependent variable accounted for by the firm-level. Apart from a single fixed effect represented by the intercept, the model contains three random effects (residual terms) that are specific to each hierarchical level of the analysis and therefore decompose the variance of the dependent variable into three independent components (the random effects are assumed to follow a normal distribution with mean of zero).

Since the analysis splits the total variance of the dependent variable into three additive parts, we can calculate the share of each respective level of the analysis in percentage points (which is equivalent to the so-called intraclass correlation coefficient). Given the data, we will estimate a cross-classification of 13,035 firms nested simultaneously within 26 sectors and 13 countries. It would be clearly preferable to distinguish more sectors (and to cover more countries in the dataset), however, the micro-aggregated CIS3 dataset from Eurostat does not allow for more detailed decomposition due to confidentiality reasons. On the other hand, empirical studies of innovation seldom venture deeper than into 2-digit industries (according to NACE, rev. 1.1), which broadly corresponds to the classification used here (see Figure 2 for definition of the sectoral breakdown).

Table 7 provides results of the decomposition for the four main ingredients of innovation strategies derived from the factor analysis in Table 6. For the sake of transparency, we report results based on four procedures. ANOVA estimates are robust to moderate departures from the normality assumption, whereas maximum likelihood estimators, although generally more accurate, require the residual term to be normally distributed.[8] The main difference between the Type I versus Type III sum of squares and the full versus restricted procedures is that the latter variants of the methods are more appropriate to nature of the data and/or specification of the model in this paper, so that we put more confidence on results of these more complex estimates (for details on the methods see Norusis, 2004).

A brief inspection of the results, however, reveals that the main outcome is robust to the different procedures. The analysis quickly leads to the conclusion that most of the variance (from 83% to 95%) is given by heterogeneity at the firm-level. Only a small fraction is accounted for by industries (from 3% to 10%) and equally little by countries (from 2% to 11%). Note that even if the contributions to variance by countries and sectors are low, this contribution is significant. In other words, the ANOVA tests that are associated with this decomposition of variance are significant at the usual levels of significance. This means that, as the literature has posited, there are significant differences between countries and sectors. But it is also true that an aggregate of the data into these categories hides away 80-90% of the variance between firms.

Table 7: Results of the variance components analysis for the 2nd stage factor scores (% of the total variance)

	Industry	Country	Firm	Industry	Country	Firm
	ANOVA Type I:			ANOVA Type III:		
Research	9.8	3.3	86.9	9.7	3.3	87.1
User	6.3	10.7	83.0	5.5	10.8	83.7
External	2.5	2.1	95.4	2.5	2.1	95.4
Production	8.5	3.1	88.4	6.8	3.2	90.1
	Full Maximum likelihood:			Restricted Maximum likelihood:		
Research	9.3	6.8	83.9	9.3	6.8	83.9
User	8.7	5.1	86.2	8.7	5.1	86.2
External	2.8	3.6	93.6	2.8	3.6	93.6
Production	7.7	2.1	90.2	7.7	2.1	90.2

Note: Analysis weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327).

It may be objected (especially by those attached to the idea that sectors and countries are important) that the results are driven by the transformation of the variables in the factorial procedure. Therefore we further investigate sensitivity of the analysis to use of variables from different stages of the factor analysis. Since the maximum likelihood procedures involve the distributional assumptions, and these variables are not normally distributed, we use only the ANOVA (Type III) method for this purpose, although again results for the different methods came out quite similar. Tables 8 and 9 put forward the estimates for the 1st stage factor scores and the original CIS3 variables, respectively. Overall the analysis strongly supports the previous conclusion. Not more than about 25% of the total variance is ever jointly attributed to the higher levels of the analysis (sectors and/or countries).

[8] It should be stressed that an important advantage of using the hierarchical approach to factors analysis in this context is that the variables generated from the 2nd stage estimates are not far from being normally distributed (despite the dataset contains only binary and/or Likert scale variables).

Table 8: Results of the variance components ANOVA (Type III) analysis for the 1st stage factor scores (% of the total variance)

	Industry	Country	Firm
R&D	7.5	2.6	89.9
Marketing	2.5	17.0	80.5
External inputs	2.9	2.4	94.7
Product effects	3.2	2.5	94.3
Process effects	8.2	0.9	90.9
Environment and standards	5.8	3.1	91.2
Information from science	5.6	2.0	92.4
Information from clients and industry	3.0	4.1	92.9
Information from suppliers and events	2.9	1.2	95.8
Formal protection	5.5	2.2	92.3
Informal protection	6.8	4.8	88.4
Non-technological innovation	2.1	3.5	94.4
Innovation co-operation	3.3	4.3	92.4

Note: Analysis weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327).

Differences between industries account for the largest proportion of the total variance for variables that are associated to the underlying technological nature of the innovation process, such as the frequency of internal R&D activity (12.6%), environmental, health and safety aspects (8.5%), effects on production capacity (7.9%) and the propensity to patent (7.2%). Also not surprising is the fact that the national context matters most for variables that are somewhat related to the quality of local demand and/or competitive environment (or a role of the so-called lead markets), such as the propensity of firms to devote resources to design (20.8%) and market introduction of innovations (8.7%) or the protection by the lead-time advantage on competitors (8.2%). The direction of these findings is well in line with the literature, but the magnitude of these contextual effects remains very low.

Table 9: Results of the variance components ANOVA (Type III) analysis for the CIS3 variables (% of the total variance)

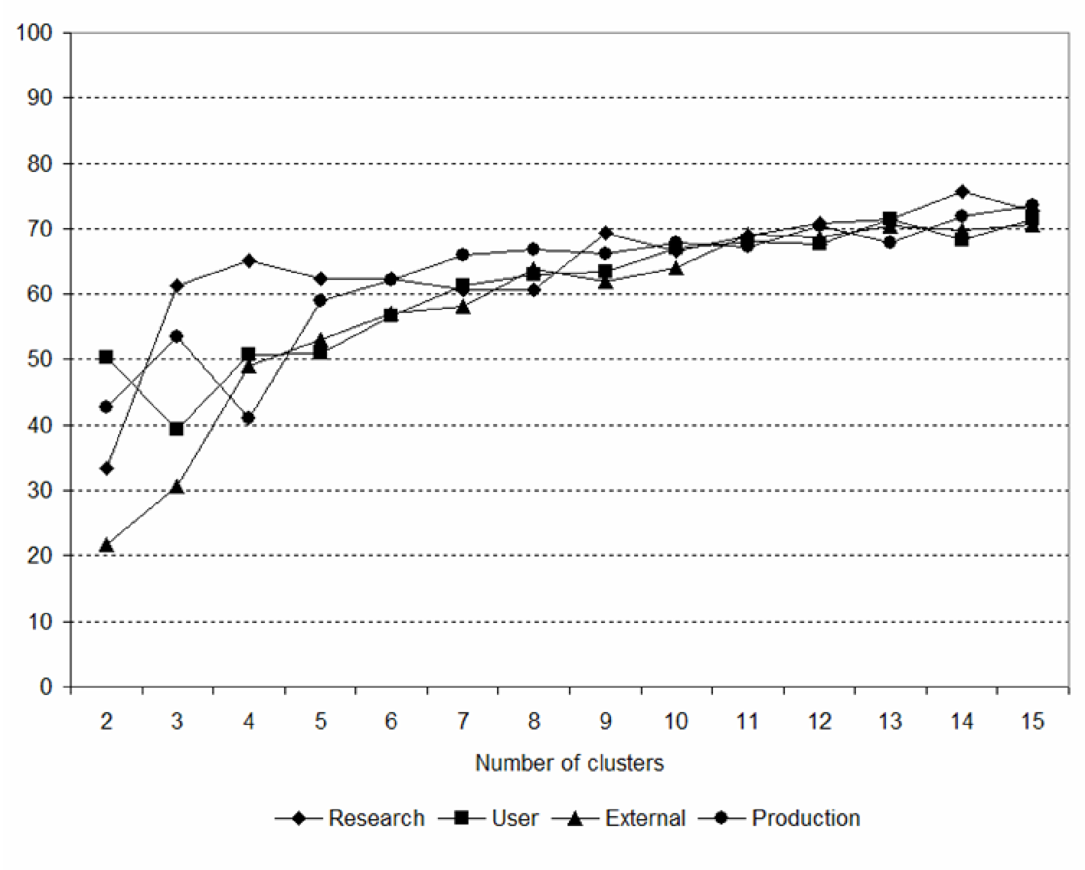
	Industry	Country	Firm
Internal R&D	12.6	3.5	84.0
Acquisition of extramural R&D	4.3	1.7	94.0
Acquisition of machinery and equipment	3.3	4.5	92.2
Acquisition of other external knowledge	3.6	0.8	95.6
Training	3.0	5.1	91.9
Market introduction of innovations	2.9	8.7	88.5
Design and other	1.7	20.8	77.5
Increased range of goods or services	3.4	2.9	93.7
Increased market or market share	3.3	1.9	94.8
Improved quality in goods or services	1.2	1.5	97.4
Improved production flexibility	6.3	0.8	92.9
Increased production capacity	7.9	1.7	90.4
Reduced labour costs per produced unit	5.9	0.3	93.8
Reduced materials per produced unit	5.9	1.8	92.4
Environmental, health and safety aspects	8.5	2.1	89.3
Met regulations or standards	2.4	3.9	93.7
Within the enterprise	2.7	1.4	95.9
Suppliers	2.0	2.7	95.3
Clients or customers	4.5	4.5	91.0
Competitors or firms in the same industry	1.2	3.8	95.0
Universities and other higher education	5.5	2.5	92.0
Government or non-profit research institutes	3.0	2.4	94.6
Professional conferences, journals, etc.	3.7	3.1	93.2
Fairs and exhibitions	6.0	2.3	91.7
Patents	7.2	2.6	90.1
Registration of design patterns	3.2	2.4	94.4
Trademarks	4.7	0.9	94.4
Copyright	4.4	1.3	94.3
Secrecy	5.4	4.5	90.1
Complexity of design	4.8	1.8	93.5
Lead-time advantage on competitors	5.8	8.2	86.0
Strategy	1.8	2.6	95.6
Management	1.4	1.7	96.9
Organisation	1.8	2.3	95.9
Marketing	2.3	2.7	95.0
Aesthetic (or other subjective) changes	2.2	3.3	94.5

Note: Analysis weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327).

6. Are there more relevant groups?

Sectors and countries do not explain very much, but this does not mean that there are no relevant contextual factors. It may well be that other grouping of firms, which have remained "hidden" behind the data so far, can actually explain a much larger proportion of the total variance. Although we cannot test for explanatory power of a deeper industrial classification or spatial differences at the regional level due to the limited information in the dataset, we can detect the most relevant grouping of firms with the help of cluster analysis.

Figure 1: Results of the variance components ANOVA (Type III) analysis by number of clusters (% of the total variance explained by clusters on vertical axis)



Note: Analysis weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises; number of observations is 13,035 (sum of weights is 105,327).

Figure 1 presents results of the decomposition exercise if the cross-classification by industries and countries is replaced by an increasing number (from 2 to 15) of K-means clusters. On the vertical axis is the proportion of the total variance attributed to the clusters (the firm-level residual accounts for the remaining percentages), while the horizontal axis depicts the number of clusters. As can be expected, the proportion of variance accounted for by the clusters tends to be an increasing function of the number of clusters, but this positive relation levels off after about 5 clusters. Moreover, from 5 clusters onwards, the solution across the different ingredients converges to fairly similar proportions. The fact that more than 50% of total variance is attributed to the 5 clusters (70% if we distinguish 15 clusters) indicates that, indeed, there are important regularities in how firms innovate. In other words, some relatively powerful contextual effects must be lurking below the surface of our sector and country classifications. These categories largely cut across the traditionally established distinctions between sectors and countries.

Note that the combinations of innovation strategy ingredients that we find in the clustering procedure are the closest we can get to identifying innovation strategies. The clusters present relatively homogenous patterns of behaviour, in which aggregation over firms does not lead to a tremendous loss of information (in any case a much smaller loss than in the aggregation over countries or sectors, even if we have a much smaller number of clusters than we have either sectors of countries). So how can we describe these clusters or innovation strategies? Table 10 reports the solution with five clusters, which seems to be representative of the overall results. Columns represent average factor scores on the four main ingredients of the innovation process, while rows pinpoint the five innovation strategies that have been delineated by the cluster analysis.[9] On the two extremes of the five clusters, we find one high profile group, which has high scores in each of the four ingredients, but especially in research, and a low profile group, which has low scores in all four ingredients (but especially in External and Production).

The other three clusters are more "specialized" in terms of the innovation strategy ingredients. The cluster that we label as User-driven scores high on the User ingredient, but also on Production. The Externally-sources cluster combines high scores on External and Production, and finally what we call the opportunistic cluster scores high on External.

Table 10: Identification of the five innovation strategies (K-means clusters)

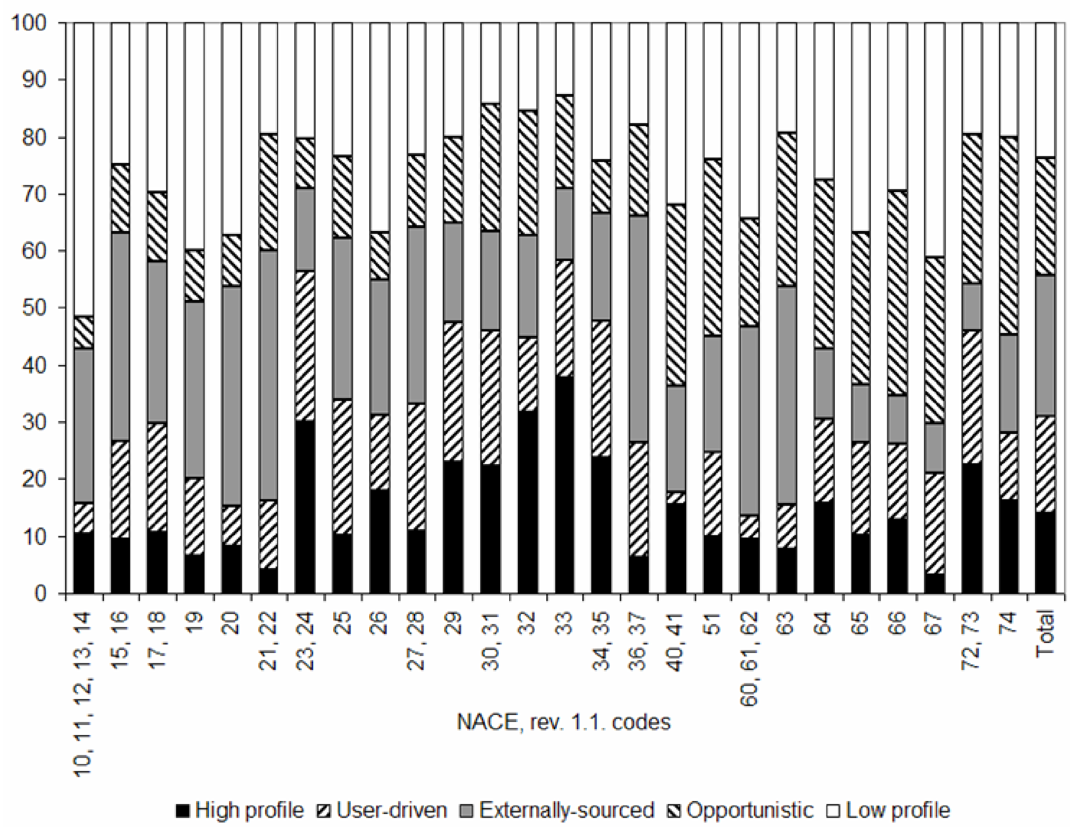
Strategy \ Ingredient	Research	User	External	Production
High profile	1.78	0.63	0.30	0.18
User-driven	-0.02	0.84	-0.84	0.63
Externally-sourced	-0.44	-0.16	0.77	0.87
Opportunistic	-0.34	0.28	0.49	-0.91
Low profile	-0.28	-1.04	-0.78	-0.68

Note: Averages weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises.

Following Leiponen and Drejer (2007), we further investigate the distribution of the firms over combinations of the 5 clusters and the 26 NACE industries. This provides an overview of the overlap between distribution of the innovation strategies and the standard industrial classification. The purpose is to allow for a direct comparison by presenting the results in a similar format to their paper. Figure 2 reports these cross-tabulations. Each bar shows the percentage of observations that fall into the particular innovation strategy by (NACE, rev. 1.1) industry.

[9] Note that the factoring procedure involves standardization of the variables (deducting mean and dividing by standard deviation), so that the factor scores have average of zero and standard deviation of one. From this follows that the average score above (below) zero for the particular cluster indicates bias towards (against) adoption of the ingredient.

Figure 2: Distribution of innovation strategies by industry and cluster



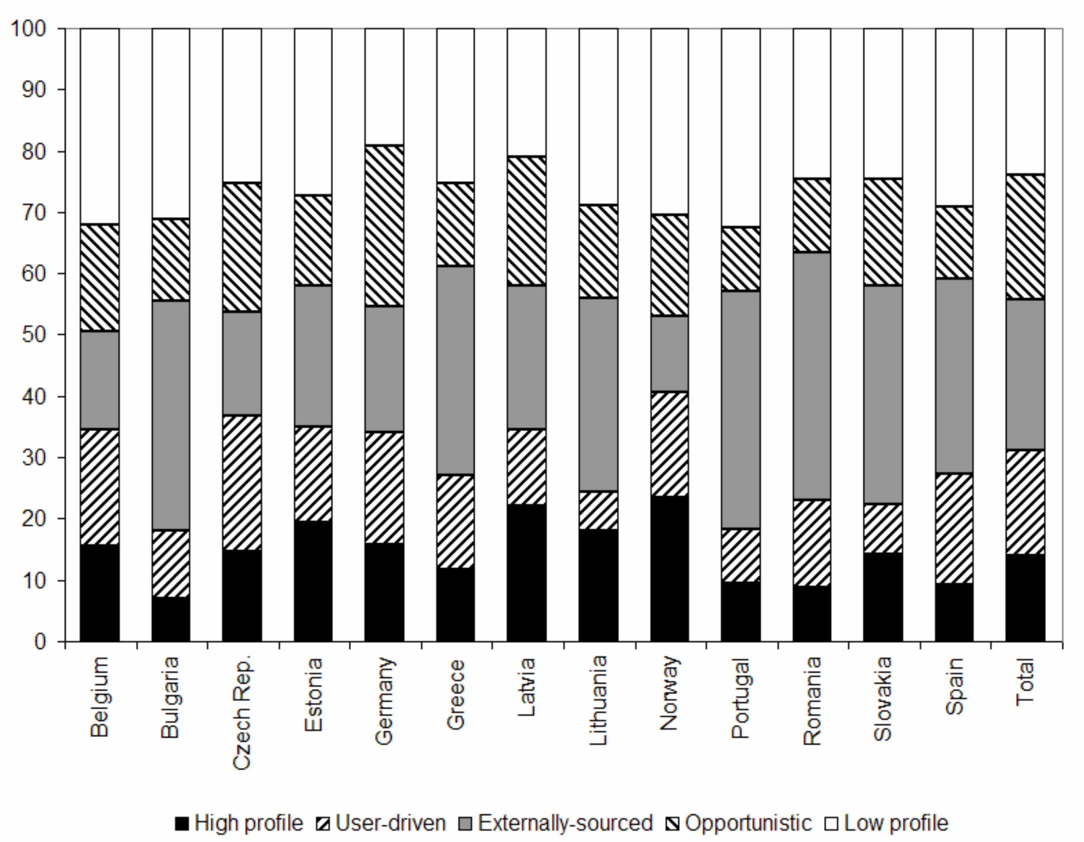
Note: Observations weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises.

We stress at the outset of the discussion of this graph that the differences between sectors in terms of the frequencies at which the five innovation strategies (clusters) are found, are statistically different. In other words, when we aggregate the firm-level occurrence of the strategies into sectoral averages, these averages are significant in a *t*- or other statistical test. However, as the figure clearly shows, this does not imply that intra-industry diversity in innovation strategy is not important. In fact, the figure confirms the finding by Leiponen and Drejer (2007) that industries tend to be very mixed bags of innovation strategies, as already confirmed by the econometric analysis above. None of the bars is anywhere close to be uniform and we find at least some firms from each of the five clusters in each industry. Most bars are rather equally distributed, and in all industries, there are at least two strategies that have more than 25% of all firms in the industry. In half of the industries, the most frequent strategy does not exceed a 33% proportion. Moreover, we do not find strong support for any systematic difference in how firms innovate between manufacturing and service sectors. Even true believers in the traditional sectoral patterns of innovation should by now start to question the conventional wisdom along these lines.

Similarly, Figure 3 depicts the distribution of the innovation strategies by country, and hence it gives us an idea of how homogenous countries are in terms of the innovation strategies of their firms. Again, an ANOVA-test confirms that the frequencies of innovation strategies differ between countries, but this does not imply that countries and strategies can be mapped on a one-to-one basis.

The last bar in these figures displays the overall distribution of the sample. This shows that firms adopting the high-profile strategy, which is the only one based predominantly on the research ingredient, are clearly a minority. This underlines the importance of analyzing innovation as something that goes well beyond an R&D strategy.

Figure 3: Distribution of innovation strategies by country and cluster



Note: Observations weighted by the inverse of the sampling fraction, corrected for non-response and for no longer existing enterprises.

7. Conclusions

Just like the Beagle allowed Charles Darwin to unravel the variety of species across the globe, and, on the basis of this evidence, to formulate his theory of evolution, our journey into the depths of community innovation survey data inevitably leads to the conclusion that 'heterogeneous' is the adverb that shall be used to analyze the innovation process. Indeed, a prosperous innovation system will resemble the variety of a rainforest rather than an Arctic wasteland. Evolutionary economic theory has been prominent in taking this heterogeneity serious, but we have argued that it still has not gone far enough in this respect.

A somewhat less poetic but more pointed summary of our results is that there is a considerable diversity in how firms innovate, and that these differences remain very substantial once we cancel out effects due to different sectoral and national contexts. Using hierarchical factor analysis, we find four distinct ingredients of the innovation process, and the variety in the intensity of use of these ingredients is an order of magnitude larger within sectors and countries than between them. By looking deeper into the issue with the help of the variance decomposition analysis we revealed that firm-level heterogeneity is the dominating tendency in the data. The four ingredients also show that what firms need and use to innovate goes far beyond an internal R&D department.

Although patterns in sectoral averages of various innovation indicators appear in our data as significant, our findings thus indicate that the literature on sectoral innovation systems tends to downplay too much the importance of differences between firms. Because sectors do not account for much difference in how firms innovate, sectoral taxonomies of innovation, which are based on data at the sectoral level, must be even less relevant. We therefore give a strong warning against a mechanistic replication of taxonomies based on sectoral data. A similar conclusion can be stated for the idea of national systems of innovation.

Admittedly, although the micro dataset covers 13 countries, which is much more than any other paper in this field, we are only able to take into account a relatively small part of the diversity across countries in the world economy. From this point of view, it should not be surprising that the country level does not come out importantly, because all countries in the analysis were either members of the European Union or on a path to the membership when the surveys was conducted. It might well be that importance of the country level would appear much higher if a more diverse set of countries in terms of institutions, policies and other relevant factors could have been included in the analysis.

As has been shown by the analysis, the finding that industries and countries do not account for much of the observed heterogeneity does not mean that there are no relevant similarities in how firms innovate. Using cluster analysis we detected grouping of firms that proved to be highly relevant for stripping the firm-level heterogeneity shroud from the data (they capture around half of the variance). We interpret the five clusters that we found as typical innovation strategies that firms apply. This suggests that the regularities in how firms innovate cut across the traditional breakdowns by industries and countries. Unfortunately, due to limits of the dataset, we were not able to find out whether this cross-cut is related to subnational regional differences, or lower levels of the NACE sectoral classification than what we used. Hence, testing our research questions with different units of sectoral and geographical aggregation remains an important task for future research.

How are we to theoretically ascertain these results? We accepted that an evolutionary framework seems to be the most relevant one for analyzing innovation, and as our review concluded, this theory has convincingly argued that heterogeneity between firms will result from the process of strategy formation at the firm level. But the question why selection has not weeded out this heterogeneity, and hence led to more homogeneity of innovative behaviour, has largely been ignored. Our results show that even within relatively partitioned selection environments, like sectors and countries, selection has not led to any homogenous outcome. This reinforces the relevance of an evolutionary perspective, but it also points in the direction of new research questions. After all, the question that emerges from our analysis is diametrically opposed to the one that is usually asked, which is what are the factors that account for the relatively homogenous nature of innovation strategies within sectoral or national systems of innovation.

We gave three reasons for heterogeneity resulting from selection in Section 2.2 (variability of the environment, neutrality, and a mixed strategy outcome). Since firms interact with each other in a direct way, both in terms of transactions and in terms of strategic reactions, co-evolution is likely to play a large role in any theory that may explain our results. Co-evolution is related to the idea of variability of the selection environment, since it may be argued that many aspects of the selection environment in economics are endogenous, i.e., related to the actions of other firms. But especially the third option, i.e., a mixed strategy outcome at the population level, seems a good candidate to bring out the relevance of co-evolution for our results. In this respect, the distinction between offensive and imitative innovation strategies may be useful. Such strategies may be relevant in every sector, and the two strategies may co-evolve with each other because of the positive feedback they may have on each other. Offensive innovators obviously provide targets for imitators, but imitators may also reinforce the success of technologies introduced by radical innovators by means of Schumpeterian bandwagon effects. Hence the two strategies may co-evolve, which is in line with our characterization of mixed strategies at the industry level. For such an explanation to become credible, however, it remains to be investigated how the four innovation strategy ingredients, and the five clusters that we identify are related to innovative vs. imitative behaviour.

The potential for neutral evolution as an explanation of heterogeneity seems at first sight to be in contrast to the idea that innovation matters for firm performance. After all, if firms innovate to survive, how can it be explained that evolution is neutral? On the other hand, much of the work that has tried to test whether economic selection of firms is related to variables like profitability of labour productivity, has concluded that such effects are weak (see, e.g., Coad, 2007 for a discussion and results). In other words, economic selection may work on other factors than financial indicators. This increases the relevance of the idea of neutral evolution as a result of the existence of many niches in the fitness landscape (i.e., a very complex landscape, in the terms of Kaufman, 1993). Such a view is certainly compatible with the importance of product innovation-related motives in innovation strategies that we identified. Our results thus suggest that the quantitative work on the selection mechanism in economics should extend their use of indicators into the innovation domain, thereby investigating the empirical relationship between our innovation strategies and firm performance.

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