Observable factors of innovation strategy

Observable factors of innovation strategy:

Firm activities and industry effects

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Abstract

Responding to research questioning the significance of external factors such as industry and country in explaining the patterns of innovation-related activities, we examine the effects of factors both internal and external to the firm. Analyzing CIS data, we find that external factors are more helpful in explaining innovation strategies than internal factors. Our econometric model can quite adequately predict innovation strategies, implying that firm-specific factors might not dominate other factors as strongly as suggested by some prior studies.

Keywords: innovation; innovation strategy; sectoral analysis; national innovation systems; sectoral innovation systems
JEL codes: O31, O32, O33, L21, C31, C38

1 Introduction

What factors do firms take into consideration when making choices about their approaches to technological innovation and the acquisition of knowledge needed in the innovation process, and how are they influenced by the characteristics of their environments? A number of innovation scholars have looked at what they have called variously "technology strategy" (see, e.g., Ford, 1988; Adler, 1989; Pavitt, 1990; Dodgson, 1991; Drejer, 1991), "innovation strategy" (Srholec and Verspagen, 2012; Clausen et al. 2011), "innovation orientation" (Prajogo et al. 2013, Yu and Lee 2017), or "innovation mode" (Lundvall, 2007; Jensen et al., 2007). Some have suggested that industry (Zahra, 1996; Malerba, 2005) and/or the related technology (Lee, 2005; Hekkert et al. 2007) is important for the way firms innovate. Others have stressed the national dimension (Lundvall, 2007), whereas for startups, a large literature studies the individual background and the knowledge base of the entrepreneurs (Hsu 2008). More recently, however, Srholec and Verspagen (2012) have argued that factors such as industry and country account for a very small proportion of the variance among firms with respect to the patterns of their innovation-related activities, implying that the key explanatory factors for the relevant choices lie in the realm of (largely unobserved) properties of the firms themselves. In this context, this paper aims to answer the question to what extent firms' innovation strategies can be explained by observable factors, including those internal and external to the firm**.** This may have important implications for whether the national or sectoral innovation system frameworks provide valuable insights for innovation policy.

In our analysis, we investigate the variation in innovation strategies and examine to what extent it can be attributed to observable characteristics of firms and their environments. To do so, we use data from the 2014 edition of the Community Innovation Survey (CIS) of European manufacturing and services firms and apply factor analysis and regression analysis ('the Eurostat CD-Rom'). Our choice of methodology seeks to maintain as clear a boundary as possible between theory and empirics; in particular we construct theory-guided measures of innovation strategy dimensions. Then we estimate a multivariate probit model of strategy indicators and assess its explanatory power by analyzing carefully a number of measures of fit.

The paper is organized as follows: In section 2 we consider the relevant theoretical issues and develop our research questions. In section 3 we present our data and methodology. In section 4 we present our results. Section 5 concludes.

2 Background and research questions

2.1 What is innovation strategy?

As with any strategy, innovation strategy concerns strategic choices, and attempts to define innovation strategy vary widely in terms of which types of choices are studied. For Bhoovaraghavan et al. (1996) and Cheng et al. (2010), innovation strategy is about the choice between process and product innovation. For Turut and Ofek (2012) and Chen and Turut (2013), it is about the choice between radical and incremental innovation. For Prajogo et al. (2013), "innovation orientation" is about whether firms are oriented toward exploratory or exploitative innovation. And for Eesley et al. (2014) and Sharif and Huang (2012), innovation strategy simply refers to the choice whether to innovate or not.

Instead of identifying strategy dimensions, some authors focus on the typical strategies firms might adopt. Lundvall (2007) and Jensen et al. (2007) distinguish between the "STI [science, technology, and innovation] mode of innovation", based on formal R&D activities in basic and applied scientific research and focused on the production of explicit, codified knowledge, and the "DUI [doing, using and interacting] mode of innovation", which is more experiential and focused on the sharing and reproduction of tacit knowledge and often involves organizational arrangements that stimulate incremental process innovation. Lundvall (2007) writes that the latter has been neglected by innovation research, which has tended to focus on the former, and argues – taking a cue from Mathews (2001) – that an appreciation of the role of DUI innovation is important for understanding learning processes in the economy.

The distinction between these two fundamental types of approaches to innovation runs through much of the thinking about innovation strategy.

Does the STI-DUI dichotomy hold empirically? Prior research suggests that it does, at least in general terms. Srholec and Verspagen (2012), Clausen et al. (2012), and Szczygielski and Grabowski (2014) all distinguished clusters of firms, of which one or two can be interpreted as varieties of the STI mode of innovation, while others can be perceived as subcategories of the DUI type. In fact, the hierarchical factor analysis applied by Clausen et al. (2011) made it possible to formally confirm this interpretation, as the authors demonstrated that the number of clusters could be reduced by joining the clusters from previous rounds to finally arrive at two types of innovation strategies: "high profile" (STI-like) and "low profile" (DUI-like).

As will be seen in section 4, we adopt elements of a number of these prior approaches to innovation strategies, as we examine such choices as radical vs. incremental innovation, process vs. product innovation, and the STI vs. DUI types of innovation.

2.2 The external factors of innovation strategy

The firm's external environment, including customers, competitors, suppliers, government, technological conditions, etc., has often been invoked in the literature as an explanation for the decisions of firms and their success.

Authors in evolutionary economics have sought to classify industries and related firm strategies according to their technological characteristics. The classic Pavitt (1984) taxonomy rests on the criterion of the technology regime of the industry. This framework goes back to the concepts of technological paradigm and technological trajectory proposed by Dosi (1982): at each moment some major technological advances (which may be more or less recent) have different effects on technological opportunities in different sectors. This in turn defines the technological trajectory – the direction of technological progress in the industry and the means of attaining it. It seems reasonable to expect that the technological trajectory or regime affects industries' innovation strategies. Taxonomical exercises are therefore a natural step in the analysis of those strategies (and in particular in examining the external factors of those strategies), especially in view of the related work on sectoral systems of innovation reviewed in Malerba (2005), situating the firm's choices about technological development and innovation in the context of the industry in which it is active.

In this paper, we largely follow Castellacci's (2008) extension of Pavitt's taxonomy, since it encompasses both manufacturing and service industries.[1] In his version, two criteria are considered: the technological content and the place

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It is important to note that Castellacci's use of terms differs from ours; for example, he identifies taxonomic groups with innovation modes.

of the industry as provider and/or recipient of advanced products, services and knowledge. The taxonomic groups are the following (note the abbreviations we use subsequently in the paper):

1. *Advanced knowledge providers* (further divided into *specialized supplier manufacturing* or *SSM*, and *knowledge-intensive business services* or *KIBS*);

2. *Mass production goods* (*science-based manufacturing*, *SBM*, and *scale-intensive manufacturing*, *SIM*);

3. *Supporting infrastructural services* (*network infrastructure services*, *NIS*, and *physical infrastructure services*, *PhIS*), and

4. *Personal goods and services* (*supplier-dominated manufacturing goods*, *SDM*, and *supplier-dominated services*, *SDS*).

The two first groups are regarded as technologically sophisticated. Advanced knowledge providers consist of SSM industries that produce specialized machinery, equipment and precision instruments, mainly for mass production industries. Within the services sector, the KIBS group consists of the industries such as consulting, R&D, software or design, which can also be classified as providers of sophisticated technological content. Mass production goods industries generate advanced technology for their own use; however, the specific nature of innovation differs between the two subgroups of this category: while SBM relies on contacts with the science sector for knowledge utilized in the innovation process, SIM is more likely to work with providers of specialized machinery and equipment.

Firms from the third group provide ‘supporting infrastructure’ for other businesses (even though they cater to individual clients too) and are characterized by a relatively low degree of own technological efforts. Castellacci draws a distinction between PhIS (logistics, wholesale trade) and NIS (finance and telecommunication), arguing that the latter represent a higher level of technological sophistication; however, both subgroups largely rely on other sectors for the provision of advanced technologies. This is particularly pronounced in the last group – personal goods and services – which is the least technologically advanced.

A number of external factors are related in one way or another to the country in which the firm operates. Benefiting from more qualified workforces, better knowledge infrastructure, and more demanding customers, companies in more developed countries stand better chances of introducing new products and production technology. This observation is conceptualized in the national innovation system framework (cf. Lundvall 2007, Edquist 2005), or more broadly in the work on national technological capabilities (see the reviews in Fagerberg and Srholec 2008, and Fagerberg et al. 2010) and technology clubs (Castellacci and Archibugi 2008). We therefore expect firms located in countries with better technological capabilities to be more likely to invest in

R&D, pioneer technologies, introduce radical product innovations and engage in technological forecasting more often than firms from less advanced countries.

2.3 Internal factors of innovation strategies

While the external environment obviously has an impact on firms' decisions and performance, one can also observe firms differing in these outcomes despite operating in seemingly similar conditions. Indeed, the need to explain the heterogeneity remarked upon by Marshall (cited in Laursen, 2012), and which tends to fly in the face of neo-classical assumptions that there is only one efficient way to do things and all inefficient ways are competed out of existence, was one of the most important motivations for the contribution of Nelson and Winter (1982) and the development of evolutionary economics. This heterogeneity is prominently displayed in the aforementioned finding of Srholec and Verspagen (2012) that industry and country are much less important than firm-specific factors in explaining the variance among firms with respect to the patterns of their innovation-related activities. On the other hand, they treat the unexplained heterogeneity as a black box and do not attempt to identify the factors behind it. This question is addressed by Szczygielski and Grabowski (2014), who analyze firm membership in clusters defined by the innovation activities of the firms. These clusters correspond, in fact, to innovation strategies. In their analysis characteristics such as firm size and being a member of a group of firms are significant factors in membership in the clusters, and thereby in the firms' innovation strategies.

The resource-based school in strategic management argues that the firm is successful if it is able to create and sustain some unique capabilities – i.e. resources and competences – that the competitors find hard to imitate (cf. Penrose 1959, Wernerfelt, 1984). These can lead to lower unit costs – e.g. due to superb internal logistics systems – or to the firms' ability to develop unique and innovative products. More generally, the capabilities in question, rooted in the internal environment of a firm, and the way they are orchestrated by management and other internal actors, will affect its position in the market together with the external factors considered in section 2.1 (Henry, 2008: 126, Teece 2019).

There is a large theoretical literature, most of it deriving from Schumpeter, on the relationship between technological innovation and firm size. According to the two main theories, either growth of the firm (hence their becoming large) results from successful technological innovations, which allow it to acquire market share, or innovation is a very costly and capital-intensive process which larger firms are better able to afford. In either case, there should be a positive relationship between size and (successful) technological innovation. However, the empirical evidence for such a relationship between size (or the degree of industry concentration) on one hand and innovativeness or R&D intensity on the other is often contradictory or ambiguous (Degner, 2011; Dolfsma and van der Velde, 2014). More specifically, with regard to the subject of technology strategy and its relationship to internal factors such as size and resources of the firm, Pavitt (1990:24) concluded that this strategy is "determined largely by the firm's size and the nature of its accumulated technological competences."

Sapprasert and Clausen (2012) find that firm age is an important explanatory factor for frequency and success of organizational innovation (with older firms more likely to attempt such innovation, but younger ones more likely to benefit from it). We are unable to observe firm age in our data, but size may, to some extent, proxy for age, since it is a common observation that young firms tend to either grow or exit the market (see, for example, Haltiwanger et al., 2010), making it unlikely that we could observe a considerable share of firms that are both small and old.

The governance or ownership structure of a firm is also of obvious relevance for all aspects of strategy, including innovation strategy. However, the influence of foreign ownership may be ambiguous. On the one hand, in low- and middle-income countries, foreign investors can be expected to be more liberally endowed with financial resources than the average domestically owned company and have a stronger technological base in general. However, we also know from the relevant literature that multinational companies tend to concentrate their R&D activity in their headquarters (see, e.g., Patel and Vega, 1999; Narula, 2002; Lee, 2005), meaning that the relative richness of available resources does not necessarily translate into their expenditure on R&D and other innovation-related activity within the subsidiary itself.

In light of the foregoing, one of the questions to be covered in our investigation in this paper of the role of internal factors in the firm's innovation strategy is whether resource-rich firms (in particular bigger firms and those that belong to groups of firms) are more likely to adopt more ambitious types of strategies than resource-poor firms: for this reason, we will also investigate whether such firms emphasize R&D and radical innovations. In particular, it will be verified whether foreign-owned firms tend to be more active innovators than domestically owned firms or vice versa, and to adopt the pioneer posture more frequently, and whether they do less R&D and monitor the science sector less intensively, preferring to rely for their technologies on their mother companies abroad. Finally, we will look at whether organizational innovations occur more frequently in firms that are group members and in bigger firms (because of their complexity).

3 Data and methodology

3.1 Data

Like Srholec and Verspagen (2012), we utilize the Community Innovation Survey data, which the Eurostat makes available to certified research entities (i.e., we use the 'Eurostat CD-Rom'); we look at the 2014 run of the CIS. Our dataset contains data for 14 countries, which, for the purpose of estimation, were aggregated into six categories (**Table 1**; for more information on the composition of the sample, see **Table 14** in the appendix). As explained in the previous section we expect the level of national technological capabilities to matter for innovation strategies, which is why for each group of countries we include the average rank in the European Innovation Scoreboard in 2014.[2]

Table 1. Composition of the sample by country groups

Group name	*DE_NO*	*MED*	*V-3*	*BALT*	*NEW_EU*
Countries in the group	Germany, Norway	Cyprus, Portugal, Spain	Czech Republic, Hungary, Slovakia	Estonia, Latvia, Lithuania	Bulgaria, Romania, Croatia
Share of the sample	.12	.41	.15	.06	.26
Average score in the European Innovation Scoreboard in 2013	.59	.44	.37	.34	.24

Note: V-3 stands for Visegrad group countries (Poland, the fourth Visegrad country is missing from our dataset).

Source: Community Innovation Survey 2014 and European Commission (2015).

We analyze both manufacturing and services firms that are classified in 25 two-digit industries or industry groups: this is because in our dataset some two-digit industries were merged. This is also the reason why we had to modify the Pavitt-Castellacci taxonomy and replace two of the groups in that taxonomy (specialized supplier manufacturing and science-based manufacturing) with other categories: “electrical and electronical equipment” (EEE and “chemicals and pharmaceutical manufacturing” (CPM). Finally, we add the category of miscellaneous repair and installation services (MRIS). The total of firms analyzed is 84,352; of these, 24,606 introduced product or process innovations, were in the process of introducing innovations, or had attempted to introduce them (only such firms fill in the whole CIS questionnaire; this is not the case for firms that only introduced innovations in marketing or firm organization).

Table 2 presents the composition of the sample with respect to the taxonomy applied. About 30% of the sample is composed of the low-tech groups of industries (supplier-dominated manufacturing and supplier-dominated services), and another 26% by physical-infrastructure services. At least 16% of firms operate in scale-intensive industries (the SIM category plus some firms from the CPM group). High-tech manufacturing is represented by CPM and EEE groups, which together constitute about 10% of the sample. Knowledge-intensive business services account for 15%, and network-intensive services (essentially, finance) for 3% of the sample.

Table 2. Composition of the sample by industry categories

KIBS	*NIS*	*PhIS*	*SIM*	*SDM*	*SDS*	*CPM*	*EEE*	*MRIS*

[2] Since the composition of the sample by country does not correspond to the actual composition (for example, the percentage of Spanish firms in the sample is too large), in the rest of the paper weighted estimations are conducted.

.15	.03	.26	.16	.23	.04	.03	.08	.02

Numbers in the table are fractions of the number of firms in the sample weighted by the inverse of the country shares. For the explanation of the abbreviations see sections 2.2 and 3.1. The number of observations is 84,352.

Source: Community Innovation Survey 2014

The Community Innovation Survey was first implemented in 1993. It is a joint effort of national statistical offices in the European Economic Area, coordinated by Eurostat. The methodology follows the Oslo Manual (OECD and EC, 2005).[3] Most questions refer to the three-year period preceding the circulation of the questionnaire (2012-2014, in our case), while questions on turnover and outlays refer mainly to the year of issue. Although the CIS questionnaire has been developed over many editions, its structure remains relatively stable with well-known ‘chapters’ such as ‘general information about the enterprise’, ‘product (good or service) innovation’, ‘process innovation’, and ‘sources of information and co-operation for innovation activities’.

The Community Innovation Survey includes only limited data about the participating firms, including their employment and sales as well as about whether the firm had any exporting activities or is a member of a group of firms (and if so, where the mother company is located). We use the latter information to define the dummy variables *group_DOM* and *group_FDI*, which equal 1 for firms that are members of groups and whose mother companies are located in the home country or abroad, respectively, as well as the dummy *no_group* for standalone firms. To exploit the information on the market the firms are exporting to we employ dummy variables: *market_LOC*, *market_DOM*, *market_EU*, *market_OTH*, which equal 1 if and only if the firm’s main market is the local, national, other-EU country, or other-non-EU country markets, respectively. Many studies have proved the exporting activities of firms to be correlated with higher productivity and innovation performance (e.g., Griffith et al. 2006; Hagemajer and Kolasa 2011; Peters et al. 2018). Thus, although the choice of the market does not have to determine innovation strategy, it is likely to be correlated with (latent) firm characteristics that do have an impact on company decisions.

We also use the binary variable *LARGE* which takes a value of 1 in the case of enterprises employing at least 250 workers and 0 otherwise. As one can see in **Table 3**, small and medium firms (LARGE=0) constitute about 90% of our sample.

Table 3. Composition of the sample by firm size and industry categories

	KIBS	*NIS*	*PhIS*	*SIM*	*SDM*	*SDS*	*CPM*	*EEE*	*MRIS*	*ALL*
Below 250 workers	.93	.83	.86	.88	.92	.93	.85	.86	.92	.90

[3] Since 1992 CIS-like surveys have been implemented in a number of non-EEA countries, including the US (cf. Arora et al. 2016).

At least 250 workers	0.07	.17	.14	.12	.08	.07	.15	.14	.08	.10

Numbers in the table are fractions of the number of firms in the sample weighted by the inverse of the country shares. For the explanation of the abbreviations see sections 2.2 and 3.1. The number of observations is 84,352.

Source: Community Innovation Survey 2014.

There is a much higher variability across industry groups when it comes to the extent of their internationalization and the membership in the groups of firms (cf. **Table 4**). About 30% of firms are members of either domestic or foreign groups, but this proportion is higher in case of high-tech manufacturing (CPM and EEE), knowledge-intensive business services and infrastructure services, and lower for supplier-dominated manufacturing.

Table 4. Composition of the sample by the membership in groups and industry categories

	KIBS	*NIS*	*PhIS*	*SIM*	*SDM*	*SDS*	*CPM*	*EEE*	*MRIS*	*ALL*
group_DOM	.24	.33	.21	.19	.14	.18	.23	.20	.21	.19
group_FDI	.15	.27	.09	.16	.07	.12	.24	.19	.09	.12
no_group	.61	.40	.70	.65	.79	.70	.53	.61	.70	.69

Source: Community Innovation Survey 2014

On average 22% of firms declare foreign markets to be their principal target (cf. **Table 5**), but this proportion is considerably higher for the scale-intensive and high-tech manufacturing industries (especially the CPM group). Interestingly, the KIBS firms are more domestically-oriented than services on average (however, presumably the relative high values for SDS are driven by tourism).

Table 5. Composition of the sample by firms' principal markets and industry categories

	KIBS	*NIS*	*PhIS*	*SIM*	*SDM*	*SDS*	*CPM*	*EEE*	*MRIS*	*ALL*
market_LOC	.39	.47	.41	.29	.37	.44	.16	.17	.43	.36
market_DOM	.43	.47	.30	.38	.34	.46	.50	.35	.41	.38
market_EU	.12	.04	.23	.29	.26	.07	.23	.35	.12	.21
market_OTH	.06	.02	.06	.04	.03	0.03	.10	.13	.04	.05

Numbers in the table are fractions of the number of firms in the sample weighted by the inverse of the country shares. For the explanation of the abbreviations see sections 2.2 and 3.1. The number of observations is 84,352.

Source: Community Innovation Survey 2014.

3.2 Methodology

Our work consists of three principal stages. First, we define the strategy variables. Second, we look at the factors of innovation strategies using multivariate probit model. Thirdly, we see to what extent the differences in innovation strategies can be explained by observable firm characteristics.

The process of defining strategy variables is based on the analysis of CIS 'chapters'. In particular, we run factor analyses on two chapters – "Varieties of Innovation Activities" and "Co-operation for product and process innovation activities" – and based on their results, we propose indicators describing various aspects of the innovation strategies of companies. Note that this restricts our analysis only to firms that introduced product or process innovations, were in the process of introducing innovations, or had attempted to introduce them, as only such firms answer the questions from these two CIS 'chapters'. The list of variables obtained in this way is supplemented by some additional indicators, according with the theory discussed above and prior studies of the problem. Suppose we extract K strategic variables, and let $S^1,\ldots,S^K$ be the strategy variables identified in this part of the study.

In the second stage of the study we estimate the parameters of the model explaining firms' propensity to apply a given innovation strategy. Since the values of strategy variables are observable only for a subset of firms, as explained in the previous paragraph, we apply a Heckman-type estimator in order to address the sample selection bias problem.

We start by estimating the parameters of the following probit model:

$$IN_i^* = \mathbf{x_i}\boldsymbol{\beta} + \mathbf{z_i}\boldsymbol{\gamma} + \varepsilon_i \,, \tag{1.a}$$

$$IN_i = I\left\{IN_i^* > 0\right\}, \tag{1.b}$$

where $i \in \{1,...,I\}$ indexes all firms, $\varepsilon_i \sim N(0,1)$, and

$$\mathbf{x_i} = (1, group\_DOM_i, group\_FDI_i, FIRM\_SIZE_i, market\_LOC_i, ...$$
$$market\_OTH_i, KIBS_i, .., SDS_i)$$

and, finally, z_i contains geographic control variables. Upon estimating the model (1.a)-(1.b), the inverse Mills ratio is calculated as follows:

$$IMR_i = IN_i * \frac{\varphi\left(\mathbf{x_i}\hat{\boldsymbol{\beta}}\right)}{\Phi\left(\mathbf{x_i}\hat{\boldsymbol{\beta}}\right)} - \left(1 - IN_i\right) * \frac{\varphi\left(\mathbf{x_i}\hat{\boldsymbol{\beta}}\right)}{\left(1 - \Phi\left(\mathbf{x_i}\hat{\boldsymbol{\beta}}\right)\right)} \tag{2}$$

Indicator IMR_i is then included as explanatory variables in the model of the strategy variables $S^1,\ldots,S^K$ so as to omit the sample selection bias problem (see: Heckman (1979)). More specifically, we estimate the following multivariate probit model:

$$S_n^{k,*} = \mathbf{x_n}\boldsymbol{\beta_k} + \mathbf{z_n}\boldsymbol{\gamma_k} + \lambda IMR_n + \varepsilon_n^k \,, \tag{3a}$$

$$S_n^k = I\left\{S_n^{k,*} > 0\right\} \tag{3b}$$

where $n \in \{1,...,N\}$ indexes all firms that introduced either product or process innovations, or had ongoing or abandoned innovation activities, and it is assumed that $\left[\varepsilon_n^1 \quad \varepsilon_n^2 \quad \cdots \quad \varepsilon_n^K\right]^T \sim N\left(\mathbf{0}, \boldsymbol{\Sigma}\right)$.

Since all the dependent variables are binary variables, the parameters of model (3a)-(3b) are estimated using GHK (Geweke-Hajivassiliou-Keane) smooth recursive conditioning simulator (cf. Geweke, 1992; Borsch-Supan, Hajivassiliou, 1993; Keane, 1994; Hajivassiliou, Ruud, 1994). Let us stress that vectors $\mathbf{x_i}$ and $\mathbf{z_i}$ are just a starting point. The selection of variables in individual models is based on their statistical significance. We apply a strategy ‘from general to specific’, following Davidson et al. (1978), who argued that, after starting from the most general model and subsequently imposing restrictions on it and verifying these restrictions, the appropriate specification of the model should be obtained. When this strategy is used, the most important problems associated with data mining are avoided (Lovell, 1983; Charemza, Deadman, 1997). In our case this estimation strategy implies that we start with a model including all the variables listed above and all the geographic controls. We then verify significance and exclude those variables that are not significant at the 0.05 level of significance. Industry group dummies are exempted from this procedure; i.e., even if any of the variables $KIBS$ through SDM prove insignificant in various estimations, we retain them. This is because we are particularly interested in the role the industry and market environment play in the formulation of innovation strategies.

One of our question concerns the relative importance of internal and external factors. Using empirical techniques to assess the role different variables play in the model, we start by looking at percentage of correct predictions. We regard the prediction of IN_i as correct if

$$P(\mathbf{x_i}\hat{\boldsymbol{\beta}} + \mathbf{z_i}\hat{\boldsymbol{\gamma}} + \varepsilon_i > 0) > f_i \qquad \text{and} \qquad IN_i = 1, \tag{4a}$$

or

$$P(\mathbf{x_i}\hat{\boldsymbol{\beta}} + \mathbf{z_i}\hat{\boldsymbol{\gamma}} + \varepsilon_i > 0) < f_i \qquad \text{and} \qquad IN_i = 0, \tag{4b}$$

where f_k is the fraction of observations for which we have that $IN = 1$. In words, we require that the implied probability of a given result is at least as high as the observed probability. The percentages of correct predictions for variables $S^1,\ldots,S^K$ are calculated analogously (using formulae (3a)-(3b)), and the percentage of correct predictions of the entire multivariate model is defined as the average of the percentages of the correct predictions for all the variables. Moreover, we define

FCP^{basic} :	The percentage of correct predictions for the basic model,
FCP^{group} :	The percentage of correct predictions for the model that omits variables *GROUP_DOM* and *GROUP_FDI*,
FCP^{large} :	The percentage of correct predictions for the model that omits the variable *LARGE*,
FCP^{mkt} :	The percentage of correct predictions for the model that omits variables *market_LOC, market_DOM, market_EU*, and *market_OTH*
FCP^{ind} :	The percentage of correct predictions for the model that omits industry group variables, and
FCP^{ctr} :	The percentage of correct predictions for the model that omits country dummies.

Next, for each of the above indicators we calculate the relative decline in the explanatory power of the model resulting from the exclusion of the respective variables. More specifically

$$DROP^{v} = \frac{FCP^{basic} - FCP^{v}}{FCP^{basic}} \tag{5}$$

Where $v \in \{group, size, mkt, ind, ctr\}$. Finally, we look at the following ratios:

$$RI^{v} = \frac{DROP^{v}}{DROP^{group} + DROP^{size} + DROP^{mkt} + DROP^{ind} + DROP^{ctr}} \tag{6}$$

to assess the relative role of the (groups of) variables in the basic model.

In the last stage of our study, we examine to what extent the variation in innovation strategy can be explained by firm characteristics. This is done in two ways. First, we look at the measure of the fit of our model; i.e., we look at FCP^{basic} and at the more specific, conditional measures of fit (the percentage of correct predictions for a variable S^{k}).Second, we perform an analysis of variance of innovation dimensions, an extended version of the analysis proposed by Srholec and Verspagen (2012). We use a variance components model (see Goldstein, 2003), where a firm's strategy choice is explained by the country where the firm is located, its industry, size, membership in a group and principal market. However, since ANOVA models are not appropriate for discrete variables (cf. Kao, Green, 2008), we analyze the variance of factors obtained in the first stage of the analysis (denoted F^{k}) rather than the variance of strategic variables (S^{k}). A basic variance components model is given as follows:

$$F_{n}^{k} = \omega_{n}^{k} + \alpha_{l}^{k} + \kappa_{m}^{k} + \rho_{o}^{k} + \zeta_{p}^{k} + \eta_{r}^{k} \tag{7}$$

where k is the index of the strategic variable, n is the firm, l stands for the NACE industry, m differentiates firms according to group membership (we distinguish three categories: standalone firms, members of domestic groups, and members of foreign groups), o differentiates firms according to the variable *LARGE* (cf. **Table 3**), p differentiates firms according to their country and r differentiates firms according to the dominant market (cf. **Table 5**).

4 Results

4.1 Results of factor analysis and the definition of strategy variables

We apply factor analysis to variables from two sets of questions ('chapters') in the CIS survey, namely "Varieties of Innovation Activities" and "Co-operation for product and process innovation activities". Then we use the results of the factor analysis to define the innovation strategy indicators. Our procedure is best explained by demonstrating how we apply it to the CIS chapter Varieties of Innovation Activities'. As shown in Table 6, for this chapter, three factors were extracted.[4] The variables *Internal R&D* and *Acquisition of external R&D* have the highest correlations with the first factor. On this basis we have constructed the indicator *RD*, which takes on a value of 1 for companies that have carried out internal R&D or acquired external R&D.

Turning to the correlations with the second factor, we define the variable 'Capacity Building' (abbreviated *CapB*), which takes on a value of 1 for firms that indicated having engaged in at least two of the following three activities: *Acquisition of machinery, equipment and vehicles needed for innovation purposes, Acquisition of software for innovation, Training (internal or external) for innovative activities.*

As for the third factor, it correlates strongly with the '*the activities to design or alter the shape or appearance of goods or services'* and with '*marketing for product innovations'*, and to a lesser extent with *'other preparatory activities for product and process innovations'.* Consequently, we define the variable *DESIGN* which equals one if and only if the firm claimed to be engaged in at least two of the three innovation activities.[5]

Next, to learn about the monitoring activities of firms, we analyze the question about collaborating during introducing innovations. Accordingly, we define two dummy variables.

Firstly, *MARKETS*, which equals 1 if and only if a firm cooperated with at least two of the following list of potential partners:

- other enterprises within an enterprise group,
- suppliers of equipment, materials, components or software,
- clients or customers,
- competitors or other enterprises within the sector.

Next, we define the variable *SCIENCE*, which takes the value of 1 if an enterprise cooperated with at least one partner from the following list:

- consultants or commercial labs,
- universities or other higher education institutes,
- government, public or private research institutes.

[4] In order to determine the optimal number of factors, Kaiser's eigenvalue-greater-than-one rule was used (Kaiser, 1960). In order to check the robustness of this method, optimal numbers of clusters were determined using alternative methods (see Kanyongo, 2006, for a review). The results of the selection of the optimal number of factors turned out to be stable.

[5] Note that the three innovation strategy indicators roughly correspond with factors, and we utilize each CIS question in the construction of exactly one indicator, seeking the maximum correlation with the respective factor.

Table 6. The Results of the Factor Analysis of the Varieties of Innovation Activities

Variable |	F^1	F^2	F^3
Internal R&D	.4172	.1087	.3105
Acquisition of external R&D	.7387	.1156	.1012
Acquisition of machinery, equipment and vehicles needed for innovation purposes	.1498	.4093	.1039
Acquisition of software for innovation	.2903	.3207	.1987
Training (internal or external) for innovative activities	.2109	.5109	.3345
Marketing for product innovations (including market research and advertising)	.2289	.2189	.6019
In-house or contracted out activities to design or alter the shape or appearance of goods or services	.1754	.1217	.6194
Other preparatory activities for product or process innovations, such as feasibility studies, testing, software development)	.2679	.2356	.4176

Note: Factors are listed in the heading of each column and factor loadings are reported in the table. Extraction method: principal-components analysis. Rotation method: varimax. Number of observations: 24,606 (fsee text).

Source: Community Innovation Survey 2014.

We note that the *RD* vs. *CapB* and *SCIENCE* vs. *MARKETS* distinctions fit well with Lundvall's (2007) classification of innovation strategies into STI (science, technology, and innovation) and DUI (doing, using and interacting) types. The former is based on formal R&D activities in basic and applied scientific research and focused on the production of explicit, codified knowledge, while the latter is more experimental and focused on the sharing and reproduction of tacit knowledge and often involves organizational arrangements that stimulate incremental process innovation.

We note that the above results of the factor analysis are similar (though not identical) to the results of Srholec and Verspagen (2012). However, these authors did not define their own variables and instead used the factor values as strategic variables in their analysis, a choice we will discuss later when we address the fit of the model.

To complete the definition of strategy variables, we take some questions directly from the questionnaire. The dummy variable *RADICAL* equals 1 if and only if the firm has introduced innovations that were new not only to the firm, but also to the market. Moreover, we define *PRODUCT* and *PROCESS* as dummy variables equal to 1 for firms that introduced product, and process innovations respectively. By analogy, *ORGMARKT* is a dummy that equals 1 if the firm introduced innovations in organization or marketing.

Table 7 shows the distribution of strategic dummy variables by industry group. Quite predictably, in the high-tech sector (EEE, CPM and KIBS), the values of *RD* are considerably higher than the scores on *CapB*. Interestingly, however, the two indicators have comparable averages in other industry groups although one would expect *RD* to lag behind *CapB* in low-tech sectors.

There seems to be a clear technology-related pattern when it comes to the question of the types of innovation engaged in. Product innovations are relatively more important for firms from the high-tech industries sectors than are process innovations. Organizational innovations show a quite interesting pattern. On one hand, this type of innovation activities is relatively popular in services sectors, just as the literature on service innovation suggests (see, e.g., Miles 2007). On the other hand, more technology-intensive manufacturing firms also include changes in firm organization in their innovation strategies.

The introduction of radical product innovations is a relatively rare phenomenon (only 13% of innovating firms). What is more, it differs substantially across industries: 27-28% of high-tech manufacturing firms declared that they introduced products new to the markets where they operate, whereas the corresponding figure is 15% for SIM companies, and only 5-6% of low-tech services.

Firms most frequently rely on information from customers and suppliers, and then on the information from the industry, with the science sector being least likely to serve as a source of inspiration: this percentage is particularly small for low-tech services (SDS), and exceptionally high for the chemicals and pharmaceutical manufacturing (CPM) and electrical and electronic equipment (EEE) groups. Note, however, that the EEE group scores the highest on *all* three 'monitoring' variables.

Table 7. The elements of innovation strategies employed, by industry groups

	KIBS	*NIS*	*PhIS*	*SIM*	*SDM*	*SDS*	*CPM*	*EEE*	*MRIS*	*ALL*
RD	.56	.38	.14	.45	.33	.17	.71	.64	.32	.37
CapB	.58	.70	.63	.62	.67	.58	.49	.60	.69	.62
DESIGN	.86	.86	.92	.84	.87	.90	.84	.83	.89	.87
PRODUCT	.34	.26	.09	.25	.20	.11	.46	.44	.15	.22
PROCESS	.27	.27	.14	.27	.20	.14	.39	.33	.15	.22
ORGMARKT	.40	.42	.22	.30	.27	.26	.49	.40	.24	.30
RADICAL	.23	.12	.05	.15	.11	.07	.27	.27	.09	.13
SCIENCE	.15	.09	.17	.11	.12	.08	.12	.06	.05	.10
MARKETS	.10	.09	.03	.07	.04	.02	.12	.10	.03	.06

Numbers in the table are fractions of the number of firms in the sample for whom the dummy variable equals 1, weighted by the inverse of the country shares. For the explanation of the abbreviations see sections 2.2, 3.1 and 4.1. The number of observations is 24,606 (see text).

Source: Community Innovation Survey 2014

4.2 Observable external and internal factors of innovation strategies

The results of the analysis of the factors of innovation strategies are presented in Tables 8 and 9, where we report the marginal effects (the estimation of the coefficients of the respective models (1a)-(1b) and (3a)-(3b) are presented in

Tables 15 and 16 in Appendix). It is evident that large firms are more likely to innovate, and to have a higher values of our strategy variables: the effect is strongest for *SCIENCE* and *PROCESS*, and the only exception is *DESIGN*. Being a member of domestic groups increases the probability of R&D activities by almost 15%, while for foreign groups this is only 5%, and the pattern is very similar with *SCIENCE*. The members of domestic and foreign groups of companies differ even more with respect to their focus on design and marketing innovations: the former are 10% more likely to implement them than the base group, while the latter are 9% *less* likely to do so. Finally we note that the industry effects are considerable and have the expected signs, and the same can be said about the variables describing firms' markets. In particular, selling outside the EU marks the most innovative companies.

Table 8. Marginal effects of the factors explaining whether firms engage in innovation activities: probit model (1)

	IN
LARGE	.202
group_DOM	.090
group_FDI	.076
KIBS	.054
CPM	.225
EEE	.119
MRIS	-.034
NIS	-.011
PhIS	-.125
SDS	-.090
SDM	-.041
market_LOC	-.053
market_EU	.104
market_OTH	.104
V-3	-.163
NEW_EU	-.301
MED	-.193
BALT	-.211

Note: the number of observations is 84,352.
German or Norwegian SIM firms that are not members of a group and whose principal market is the national marker are the base category.
Source: Community Innovation Survey 2014

Table 9. Marginal effects of the factors of innovation strategies: multivariate probit model (3a)-(3b)

	RD	*CapB*	*DESIGN*	*SCIENCE*	*MARKETS*	*RADICAL*	*ORGMARKT*	*PRODUCT*	*PROCESS*
LARGE	0.094	0.090	-0.009	0.143	0.095	0.086	0.129	0.120	0.159
group_DOM	0.149	0.068	0.100	0.102	0.091	0.017	-	0.027	0.169
group_FDI	0.051	0.055	-0.099	0.036	0.101	0.084	-	0.037	0.121
KIBS	0.173	0.007	0.075	0.079	0.018	0.116	0.028	0.043	-0.001
CPM	0.235	-0.014	0.135	0.096	0.014	0.032	0.048	0.115	0.104
EEE	0.179	0.058	0.082	0.053	0.018	0.102	-0.011	0.071	0.068
MRIS	-0.003	0.099	-0.065	0.005	-0.040	-0.011	-0.021	-0.042	-0.120
NIS	-0.088	0.123	-0.002	-0.049	0.082	-0.050	0.187	0.031	0.182
PhIS	-0.219	0.093	-0.078	-0.111	-0.025	-0.143	0.007	-0.093	-0.161
SDS	-0.215	-0.085	-0.103	-0.090	-0.054	-0.045	0.044	-0.061	-0.210
SDM	-0.135	-0.040	-0.065	-0.076	-0.058	-0.016	-0.018	-0.004	-0.032
market_LOC	-0.156	-0.058	-0.118	-0.088	-0.057	-0.109	-	-0.121	-0.021
market_EU	0.024	-0.012	-0.062	0.047	0.064	0.036	-0.040	0.052	0.047
market_OTH	0.208	0.127	0.159	0.114	0.035	0.098	0.067	0.073	0.049
V-3	-0.012	0.047	-0.354	-	0.080	0.061	-0.026	-0.021	-
NEW_EU	-0.327	-0.011	-0.485	-0.153	-0.061	-0.012	-	-0.077	-0.135
MED	-0.023	-0.362	0.332	0.025	-0.038	-0.043	-	-0.081	-
BALT	-0.085	0.018	-0.369	-0.009	0.083	0.086	-0.055	-0.073	0.039

Note: the number of observations is 24,606 (see text). German or Norwegian SIM firms that are not members of a group and whose principal market is the national marker are the base category.
Source: Community Innovation Survey 2014

We now turn to the relative importance of the internal and external factors of innovation strategies. ***Table 10*** refers to the model of the firm's decision to perform innovation activities or not (cf. equations (4a)-(4b) and the accompanying definitions), while **Table 11** presents the same analysis for the multivariate probit models. The variables describing firms' principal markets and group membership are the most helpful in explaining whether the firm engages in innovation activities, while external factors (industry and country) are most important in explaining the kind of innovation strategy adopted.

Table 10. The role of explanatory variables: the probit selection model

Model	FCP	Drop in explanatory power (*DROP^v^*)	Relative importance (*RI^v^*)
Basic model	.69	-	-
GROUP_DOM and *GROUP_FDI* omitted	.57	.17	.26
SIZE omitted	.68	.01	.02
market_LOC, market_DOM, market_EU, and *market_OTH omited*	.51	.26	.38
Industry group dummies omitted	.64	.07	.11
Country dummies omitted	.58	.16	.23

Note: For the definition of indicators see section 3.2 and formulae (4a)-(4b).
Source: Community Innovation Survey 2014

Table 11. The role of explanatory variables: the multivariate probit model of innovation strategy

Model	FCP	Drop in explanatory power (*DROP^v^*)	Relative importance (*RI^v^*)
Basic model	.78	-	-
GROUP_DOM and *GROUP_FDI* omitted	.72	.08	.12
LARGE omitted	.72	.08	.12
market_LOC, market_DOM, market_EU, and *market_OTH omited*	.70	.10	.16
Industry group dummies omitted	.64	.18	.28

Country dummies omitted	.62	.20	.32

Note: For the definition of indicators see section 3.2.
Source: Community Innovation Survey 2014

It should be stressed that the above exercise was about *relative* importance of internal and external factors. However we still would like to answer the question, to what extent the observable factors available in the CIS dataset can 'explain' the innovation strategies as defined in this paper. We now turn to this problem.

4.3 Can observable factors 'explain' innovation strategies?

Table 12 shows three measures of the percentage of correct predictions for both models (i.e. (1a)-(1b) and (3a)-(3b)). The overall percentage of correct predictions is between 69% and 85%, which indicates a high degree of predictive power. Importantly, the model tends to predict correctly both 'ones' (the Sensitivity column) and 'zeros' (the Specificity column): the variables that consistently tend to be the best predicted ones are *SCIENCE*, *MARKETS* and *RADICAL*. Thus, judging from the criterion of correct predictions, it seems that although the fit of the model is far from perfect, we are able to 'explain' innovation strategies to a considerable extent.

Table 12. The percentages of correct predictions for the model (1)-(4)

	Percentage of correctly predicted units	**Sensitivity**	**Specificity**
IN	69%	75%	65%
RD	72%	86%	56%
CapB	83%	88%	63%
DESIGN	71%	53%	87%
SCIENCE	84%	70%	86%
MARKETS	80%	73%	81%
RADICAL	76%	72%	78%
ORGMARKT	74%	55%	79%
PRODUCT	70%	67%	72%
PROCESS	71%	68%	73%

Note: "Sensitivity" is the probability that the prediction equals 1 conditioned on the variable being equal to 1. "Specificity" is the probability that the prediction equals 0 conditioned on the variable being equal to 0. The prediction is regarded as correct if the probability of a given result is at least as high as the observed probability.
Source: Community Innovation Survey 2014

Can this optimism be sustained if we perform an analysis of variance similar to that carried out by Srholec and Verspagen? In fact, our results for the bulk of the variance in the factors extracted in the first step of our study, while the observable factors play a minor role (Table 13).

Table 13. Analysis of variance

	Country	Industry	Size	Group	Market	Firm
F^1	11.25%	7.23%	3.78%	1.35%	2.34%	74.05%
F^2	10.79%	3.45%	.23%	.98%	.75%	83.80%
F^3	5.68%	4.50%	.26%	1.05%	.93%	87.58%

Source: Community Innovation Survey 2014

So, why does the ANOVA suggest that observable factors account for a small portion of the variance in firms' innovation strategies, while our model can predict innovation strategies quite well using precisely these factors? We believe there are at least four reasons behind this discrepancy, and which make our model more fit for purpose in assessing the weight of observable factors in explaining innovation strategy.

First, in our approach, we directly address the sample selection bias by employing the Heckman procedure (in fact, an alternative probit model that did not control for sample selection proved to be a much worse predictor than models (1a)-(3b)[6]). Second, our econometric framework makes it possible to differentiate between factors that affect innovation strategies more strongly and those whose effects are less important. Thirdly, by estimating the multivariate probit model we account for the possible correlation among the error terms, which contributes to more accurate predictions. Finally, note that our econometric model and the analysis of variance (7) differ with regard to dependent variables: while the former uses relatively simple, CIS-based indicators, the latter applies the factor values. It might be the case that, since the factor values depend on *all* the questions from the respective CIS 'chapters' (cf. Tables 5 and 6), these variables show more variation that is hard to explain by observable factors. (We illustrate the latter point by an example. Suppose there are two companies that both engage in internal R&D activities but differ with respect to some other 'varieties of innovation activities', say, marketing for product innovations (cf. Table 6). Their values of the RD variable are obviously the same, while their respective values of the factor F^1 are different.).

Conclusions

With this paper we hope to have contributed to research on the role that factors external and internal to the firm play in its innovation strategy. We applied a number of statistical techniques to the firm-level data from the 2014 edition of the Community Innovation Survey. While we build on previous work in the field, our empirical approach is novel in that we address the selection problem in the analysis of strategies, and we use the measures of fit to assess the relative role of various factors in formulating the innovation strategies.

6 Results of this alternative estimation are available on request.

We found that the external factors, such as the country and the industry in which the company operates, play a smaller role than internal factors in the decision whether to innovate or not, but they are more important in the choice of the specific strategy (e.g., based on R&D or capacity building).

In general, we have demonstrated that, if innovation strategies are measured in a relatively simple way, then the observable factors are able to explain innovation strategies quite satisfactorily. While we certainly would not wish to dismiss the heterogeneity in firms' R&D behavior, we do believe our results imply that it is important for innovation policy debates to continue to be informed by the body of work on national and sectoral innovation systems.

If this is so, we believe the future research agenda on national and sectoral systems of innovation should move from the descriptive approach that has tended to characterize much work in this area to a more analytical and comparative one. What has been seen as a framework should become a method. To accomplish this, it will be necessary to build tools for capturing characteristics of systems in ways that facilitate comparison. We agree with the call by Srholec and Verspagen (2012) for more work on disentangling sectoral and national effects from heterogeneous behavior within sectors and countries, for example by employing data aggregated at lower levels of NACE classification. Recent work by Radosevic and Yoruk (2013, 2018) provides examples of how quantitative techniques can be developed that allow for comparisons across countries (and, by extension, sectors).

References

Arora, A., W. M. Cohen, and J. P. Walsh (2016), 'The acquisition and commercialization of invention in American manufacturing: Incidence and impact', *Research Policy*, **45**(6), 1113-1128.

Adler, P. (1989), 'Technology strategy: a guide to the literatures', in R.S. Rosenbloom and R.A. Burgelman (eds.), *Research in Technological Innovation, Management and Policy*, **4**, 25-151.

Bhoovaraghavan, S., A. Vasudevan and R. Chandran (1996), 'Resolving the process vs. product innovation dilemma: A consumer choice theoretic approach', *Management Science*, **42**(2), 232-246.

Borsch-Supan, A. and V. Hajivassiliou (1993), 'Smooth unbiased multivariate probability simulators for maximum likelihood estimation', *Journal of Econometrics*, **58**(3), 347-368.

Castellacci, F. (2008), 'Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation', *Research Policy*, **37**(6-7), 978-994.

Castellacci, F. and D. Archibugi (2008), 'The technology clubs: The distribution of knowledge across nations', *Research Policy*, **37**: 1659-1673.

Charemza, W. W. and D. F. Deadman (1997), *New Directions in Econometric Practice. General to Specific Modelling, Cointegration and Vector Autoregression*. Edward Elgar: Aldershot.

Chen, Y. and Ö. Ergin Turut, (2013), 'Context-dependent preferences and innovation strategy', *Management Science*, **59**(12), 2747-2765.

Cheng, C. F., M. K. Lai and W. Y. Wu (2010), 'Exploring the impact of innovation strategy on R&D employees' job satisfaction: A mathematical model and empirical research', *Technovation*, **30**(7–8), 459–47.

Clausen, T., M. Pohjola, K. Sapprasert, and B. Verspagen (2011), 'Innovation strategies as a source of persistent innovation', *Industrial and Corporate Change*, **21**(3), 553-585.

Davidson, J. H., D. H. Hendry, F. Srba and S. Yeo (1978), 'Econometric Modelling of the Aggregate Time-Series Relationship Between Consumers' Expenditure and Income in the United Kingdom', *Economic Journal*, **88**, 661-692.

Degner, H. (2011), 'Do technological booms matter? New evidence on the relationship between firm size and innovativeness', *Cliometrica*, **5**(2), 121-144.

Dolfsma, W. and G. van der Velde (2014), 'Industry innovativeness, firm size, and entrepreneurship: Schumpeter Mark III?', *Journal of Evolutionary Economics*, **24**(4), 713-736.

Dodgson, M. (1991), 'The management of corporate technology strategy', *International Journal of Technology Management* (Special edition on the *Role of Technology in Corporate Policy*), 95-102.

Dosi, G. (1982), 'Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change,' *Research Policy*, **11**(3), 147-162.

Drejer, A. (1996), 'Frameworks for the management of technology: Towards a contingent approach', *Technology Analysis and Strategic Management*, **8**(1), 9-2.

Edquist, C. (2005), 'Systems of innovation: Perspectives and challenges', in J. Fagerberg, D. C. Mowery and R. R. Nelson (eds.), *The Oxford Handbook of Innovation*. Oxford University Press: Oxford.

Eesley, C. E., D. H. Hsu and E. B. Roberts (2014), 'The contingent effects of top management teams on venture performance: Aligning founding team composition with innovation strategy and commercialization environment,' *Strategic Management Journal*, **35**(12), 1798–1817.

European Commission (2015), Innovation Union Scoreboard 2015. DG Growth: Brussels.

Fagerberg, J., M. Srholec, M. (2008), 'National innovation systems, capabilities and economic development', Research Policy, **37**(9), 1417-1435.

Fagerberg, J., M. Srholec and B. Verspagen (2010), 'Innovation and economic development', in B. H. Hall and N. Rosenberg (eds.), *Handbook of the Economics of Innovation* (vol. 2). Elsevier: Amsterdam.

Ford, D. (1988), 'Develop your technology strategy', *Long Range Planning*, **21**(5), 85-95.

Geweke, J. (1992), 'Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments', in J. M. Bernardo, J. O. Berger, A. P. Dawid, and A. F. M. Smith (eds.), *Bayesian Statistics*, Oxford University Press, Oxford.

Goldstein, H. (2003), *Multilevel Statistical Models*. Arnold: London.

Griffith, R., E. Huergo, J. Mairesse and B. Peters (2006), 'Innovation and Productivity Across Four European Countries,' *Oxford Review of Economic Policy*, **22**(4), 483-498.

Greene, W. H. (2011), *Econometric Analysis*. 7th edition. Prentice Hall: Upper Saddle River, NJ.

Hajivassiliou, V. and P. A. Ruud (1994), 'Classical estimation methods for LDV models using simulation,' *Handbook of Econometrics*, 4, 2383-2441.

Haltiwanger, J., R. Jarmin and J. Miranda (2010), 'Who Creates Jobs? Small vs. Large vs. Young', Working Paper 16300, NBER: Cambridge MA.

Heckman, J. J. (1979), 'Sample Selection Bias as a Specification Error', *Econometrica*, **47**(1), 153-161.

Hekkert, M. P., R. A. Suurs, S. O. Negro, S. Kuhlmann, & R. E. Smits (2007), 'Functions of innovation systems: A new approach for analysing technological change' *Technological Forecasting and Social Change*, 74(4), 413-432.

Henry, A. (2008), *Understanding Strategic Management*. Oxford University Press: Oxford.

Hsu, D. H. (2008). 'Technology-based entrepreneurship', in S. Shane (ed), *Handbook of Technology and Innovation Management,* Wiley-Blackwell: Chichester.
Jensen, M. B., B. Johnson, E. Lorenz and B.-Å. Lundvall (2007), 'Forms of knowledge and modes of innovation', *Research Policy,* **36**(5): 680-693.
Kaiser, H. F. (1960), 'The application of electronic computers to factor analysis', *Educational and Psychological Measurement,* **20**, 141-151.
Kanyongo, G. Y. (2005), 'The Influence of Reliability of Four Rules for Determining the Number of Components to Retain', *Journal of Modern Applied Statistical Methods,* **5**(2), 332-343.
Kao, L. S. and C. E. Green (2008), 'Analysis of variance: Is there a difference in means and what does it mean?' *Journal of Surgical Research,* **144**(1), 158-170.
Keane, M. (1994), 'A Computationally Practical Simulation Estimator for Panel Data', *Econometrica,* **62**(1), 95-116.
Laursen, K. (2012), 'Keep searching and you'll find: What do we know about variety creation through firms' search activities for innovation?' *Industrial and Corporate Change,* **21**(5), 1181-122.
Lee, K. (2005), 'Making a Technological Catch-up: Barriers and opportunities' *Asian Journal of Technology Innovation,* **13**(2), 97-131.
Lovell, M. C. (1983), 'Data mining', *Review of Economics and Statistics,* **65**, 1-12.
Lundvall, B.-Å. (2007), 'National Innovation Systems — Analytical Concept and Development Tool', *Industry and Innovation,* **14**(1), 95-119.
Malerba, F. (2005), 'Sectoral Systems: How and Why Innovation Differs across Sectors', in J. Fagerberg, D.C. Mowery, & R.R. Nelson (eds.), *The Oxford Handbook of Innovation,* Oxford University Press: Oxford.
Mathews, J. A. (2001), 'National systems of economic learning: the case of technology diffusion management in East Asia', *International Journal of Technology Management,* **22**(5/6), 455–479.
Miles, I. (2007), 'Research and development (R&D) beyond manufacturing: the strange case of services R&D', *R&D Management,* **37**(3), 249-268.
Narula, R. (2002), 'Innovation systems and 'inertia'in R&D location: Norwegian firms and the role of systemic lock-in', *Research Policy,* **31**(5), 795-816.
Nelson, R. R. and S. G. Winter (1982), *An evolutionary theory of economic change*. Harvard University Press: Cambridge MA.
OECD (2005), *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data*. OECD: Paris.
Patel, P. and M. Vega (1999), 'Patterns of internationalisation of corporate technology: Location vs. home country advantages', *Research Policy,* **28**(2-3), 145-155.
Pavitt, K. (1984), 'Sectoral patterns of technical change: Towards a taxonomy and a theory', *Research Policy,* **13**(6), 343-373.
Pavitt, K. (1990), 'What we know about the strategic management of technology', *California Management Review,* **32**(3), 17-26.

Penrose E, (1959) *The Theory of the Growth of the Firm*, New York, John Wiley and Sons.

Peters, B., R. Riley, I. Siedschlag, P. Vahter, J. McQuinn, (2018), ‘Internationalisation, innovation and productivity in services: evidence from Germany, Ireland and the United Kingdom’. *Review of World Economics*, **154**(3), 1-31.

Prajogo, D. I., C. M. McDermott and M. A. McDermott (2013), ‘Innovation orientations and their effects on business performance: contrasting small- and medium-sized service firms’, *R&D Management,* **43**(5), 486-50.

Radosevic, S., Yoruk, E. (2013), ‘Entrepreneurial propensity of innovation systems: Theory, methodology and evidence, *Research Policy,* **42**(5), 1015-1038.

Radosevic, S., Yoruk, E. (2018), ‘Technology upgrading of middle income economies: A new approach and results’, *Technological Forecasting and Social Change,* 129, 56-75.

Sapprasert, K. and T. Clausen (2012), ‘Organizational innovation and its effects’, *Industrial and Corporate Change,* **21**(5), 1283–1305.

Sharif, N. and C. Huang (2012), ‘Innovation strategy, firm survival and relocation: The case of Hong Kong-owned manufacturing in Guangdong province, China’, *Research Policy,* **41**(1), 69-78.

Srholec, M. and B. Verspagen (2012), ‘The voyage of the Beagle into innovation: Explorations on heterogeneity, selection, and sectors’, *Industrial and Corporate Change,* **21**(5), 1221-1253.

Szczygielski, K. and W. Grabowski (2014), ‘Innovation strategies and productivity in the Polish services sector’, *Post-Communist Economies,* **26**(1), 17-38.

Tauchmann, H. (2010), ‘Consistency of Heckman-type two-step Estimators for the Multivariate Sample-Selection Model’, *Applied Economics,* **42**(30), 3895-3902.

Teece, D. J. (2019). A capability theory of the firm: An economics and (Strategic) management perspective. *New Zealand Economic Papers, 53*, 1–43.

Turut, Ö., and Ofek, E. (2012), ‘Innovation Strategy and Entry Deterrence’, *Journal of Economics & Management Strategy,* **21**(3), 583–631.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*, 171–180.

Yu, G. J. and J. Lee (2017), ‘When should a firm collaborate with research organizations for innovation performance? The moderating role of innovation orientation, size, and age’, *The Journal of Technology Transfer,* **42**(6), 1451-1465.

Zahra, S. A. (1996), ‘Technology strategy and financial performance: Examining the moderating role of the firm’s competitive environment’, *Journal of Business Venturing,* **11**(3), 189-219.

Appendix

Table 14. Composition of the sample by NACE industries and the attribution to taxonomy groups

NACE groups	Frequency	taxonomy group
10-12	.08	Supplier-dominated manufacturing (SDM)
13-15	.06	Supplier-dominated manufacturing (SDM)
16-17	.04	Supplier-dominated manufacturing (SDM)
18	.02	Supplier-dominated manufacturing (SDM)
19-21	.03	Chemicals and pharmaceutical manufacturing (CPM)
22-23	.06	Scale-intensive manufacturing (SIM)
24-25	.07	Scale-intensive manufacturing (SIM)
26-28	.08	Electrical and electronic equipment (EEE)
29-30	.03	Scale-intensive manufacturing (SIM)
31-32	.04	Supplier-dominated manufacturing (SDM)
33	.02	Miscellaneous repair and installation services (MRIS)
45-47	.16	Supplier-dominated services (SDS)
49-51	.06	Physical infrastructure services (PhIS)
52-53	.03	Physical infrastructure services (PhIS)
55-56	.02	Supplier-dominated services (SDS)
58-63	.08	Knowledge-intensive business services (KIBS)
64-66	.03	Network-intensive services (NIS)
68	.00	Physical infrastructure services (PhIS)
69-75	.07	Knowledge-intensive business services (KIBS)
77-82	.02	Physical infrastructure services (PhIS)

Source: Community Innovation Survey 2014

Table 15. Estimates of the parameters of the model explaining whether firms engage in innovation activities: probit model (1)

Explanatory variable	*IN*
LARGE	.695***
group_DOM	.310***
group_FDI	.260***
KIBS	.184***
CPM	.776***
EEE	.409***
MRIS	-.118***
NIS	-.079***
PhIS	-.432***
SDS	-.311***
SDM	-.022**
market_LOC	-.183***
market_EU	.359***
market_OTH	.359***
V-3	-.559***
NEW_EU	-1.034***
MED	.162***
BALT	-.727***

Source: Community Innovation Survey 2014

Table 16. Estimates of the parameters of the factors of innovation strategies: multivariate probit model (3a)-(3b)

	RD	*CapB*	*DESIGN*	*SCIENCE*	*MARKETS*	*RADICAL*	*ORGMARKT*	*PRODUCT*	*PROCESS*
IMR	-	2.096***	2.381***	.456***	.211*	.741***	-.405***	.798***	1.479***
LARGE	.373***	.479***	-.058**	.642***	.664***	.282***	.351***	.321***	.439***
group_DOM	.077**	.184***	.423***	.383***	.605***	.250***	-	.178***	.493***
group_FDI	-.075*	.250***	.281***	.294***	.741***	.378***	-	.284***	.349***
KIBS	.297***	.035	.632***	.229***	.081***	.254***	-.019	.344***	-.001
CPM	.630***	.713***	1.674***	.493***	.101**	.398***	-.189***	.609***	.302***
EEE	.369***	.447***	1.099***	.117***	-.185***	.400***	-.231***	.574***	.188***
MRIS	-.135***	-.184***	-.198***	-.061*	-.091**	-.352***	-.243***	-.134***	-.326***
NIS	-.071	.395***	.769***	0.024	.011	.159***	.223***	.180***	.495***
PhIS	-.394***	-.707***	-.619***	-.522***	-.466***	-.594***	.054*	-.505***	-.439***
SDS	-.562***	-.833***	-.579***	-.837***	-.605***	-.557***	.405***	-.273***	-.569***
SDM	-.160***	-.191***	.063***	-.322***	-.292***	-.110***	-.020*	-.019	-.089***
market_LOC	-.279***	-.557***	-.281***	.213***	.201***	-.107***	-	-.720***	-.070***
market_EU	.203***	.576***	.639***	.242***	.169***	.334***	-.043**	.399***	.338***
market_OTH	.342***	.692***	.782***	.400***	.168***	.571***	.075***	.458***	.348***
V-3	-1.593***	-2.568***	-2.656***	-	.436***	.096***	-.096***	-.111***	-
NEW_EU	-1.991***	-3.406***	-3.841***	-.526***	.140*	-.470***	-	-.538***	-.544***
MED	-.186***	-3.176***	-1.802***	-.147***	.193***	-.282***	-	-.590***	-
BALT	-2.057***	-3.223***	-3.197***	-.415***	.236***	-.371***	-.167***	-.548***	.153***

Source: Community Innovation Survey 2014