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Innovation patterns in manufacturing and services: sectoral-determinism or strategic-choice? A multivariate analysis of CIS-3 data

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MARC TIRI*, LUDO PEETERS and GILBERT SWINNEN

KIZOK, Research Centre for Entrepreneurship and Innovation, Hasselt University, Belgium

* Corresponding author.

KIZOK, Research Centre for Entrepreneurship and Innovation, Hasselt University, Agoralaan (Building D), BE-3590 Diepenbeek, Belgium, Tel.: ++32-11-26 86 06, Fax: ++32-11-26 87 00, E-mail: marc.tiri@uhasselt.be

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Abstract

This paper presents the results from a multivariate (factor and cluster) analysis of the variation in innovation processes of manufacturing and service firms. Using data from the third Community Innovation Survey for Flanders (Belgium), a set of seven clusters of firms that are to be interpreted as 'innovation patterns' or 'innovation strategies' is identified. Two major findings emerge: (i) the 'sectoral determinism' of innovation does not hold true for Flemish firms, since multiple innovation strategies seem to co-exist within the same industry; (ii) firms in the service industry seem to form a separate, 'low-profile' innovation cluster. The latter finding may, however, raise some issues about the 'technological bias' of CIS-3. In conclusion, we point to some important implications for the design of adequate innovation-policy measures.

1. Introduction

Innovation is a complex phenomenon, and firms' innovation activities differ in terms of composition, orientation and intensity. This complexity raises several measurement problems, which have been discussed at length in the innovation literature [1,2].[1] The Community Innovation Survey (CIS), which is firmly rooted in the same tradition as the *Oslo Manual* [3], is designed to provide a large set of new (input and output) indicators of innovation to complement the standard measures, such as R&D and patents.

In this paper, we conduct a multivariate (factor and cluster) analysis of the CIS-3 firm-level data for the region of Flanders, in Belgium. Specifically, our aim is to detect distinct strategies of innovation in the Flemish business sector, and to develop a new taxonomy of innovation.

The present study is closely related to earlier work conducted by [4-10], among others. All these studies elaborate on the concept of 'technological regimes', introduced by [11], in order to draw a link between the many facets of the innovation process as well as to establish a number of invariant categories based on the observed (dis)similarities across industries. Such a framework was considered to be more appropriate for an improved understanding of innovation processes, and should provide better guidance in designing innovation policies (e.g., [12]). According to this view, groupings of firms exhibiting a similar innovative behavior (innovation pattern) can be interpreted as groups of firms choosing a specific 'innovation strategy'.

However, the present study also differs from the above-mentioned studies in several respects. Firstly, our aim is to establish a classification of innovating *firms* rather than innovating industries; that is, we want to classify firms *directly* into taxonomical categories, without the intermediate classification into industries (see Figure 1). This contrasts sharply with Pavitt's [4] typology, which is a 'standard' point of reference in much of the literature on innovation strategies. Pavitt's typology takes as a starting point the 'sectoral determinism' of innovation (i.e., the association between types of industries and patterns of technological change). More precisely, Pavitt't typology is based on industries rather than on firms (see panel A of Figure 1). This, however, is a major limitation, because it has become clear by now that firms that have conveniently been grouped into an industry on the basis of their main output(s) may have a different technological base. To quote Archibugi in his review article [13, p. 419]: "*Both slippers and moon-boots belong to the footwear industry, but the technology intensity of the two products is very different and it is reasonable to expect that their manufacturers will use different sources to innovate*." Our approach also deviates from Pavitt's in terms of methodology, in the sense that we use a formal (statistical) procedure to identify innovation strategies among firms. In taking this approach, we hope to bypass some other important criticisms of Pavitt's typology, arguing that sectoral boundaries are not always straightforward, and that firms may display attributes of more than just one of the Pavitt-type sectors – which, then, would seriously hamper any sectoral classification of the firms [14, p. 709].

Figure 1

Secondly, [6,9,10] among others,[2] also used statistical procedures, but they confined their analysis to either manufacturing or services. Also Pavitt's initial typology was confined to manufacturing, although in his later work [15] the scope was broadened to include (at least some) services as well. From Figure 2 it can be seen that the attention in the literature has shifted over time from manufacturing to services.

To date, empirical evidence on the differences in the innovation behavior between manufacturing and service firms using an 'integrative' approach is still lacking. Therefore, in the present paper, firms from both the manufacturing and service sector are treated 'on an equal footing' and integrated into a single analytical framework in order to investigate the variation in the content and nature of the innovation processes of firms across and within both sectors. In doing so, we are able to investigate whether strategies of innovation are different in manufacturing and services, and whether a 'dichotomous approach' to study both business sectors is justifiable. Specifically, our 'integrative' approach is aimed at fully exploiting the richness of the available data from CIS-3, which was intentionally designed to open up new perspectives for this type of analysis. Conversely, the results can also be used to investigate whether future editions of the CIS need to be further adapted to account for the specificities of both sectors.[3]

$\boxed{\textbf{Figure 2}}$

The remainder of this paper is organized as follows. In Section 2, the basic characteristics of the CIS-3 data are described. In Section 3, a brief discussion of the empirical classificatory method applied is provided, together with the results of the factor (step 1) and cluster (step 2) analysis. In Section 4, a characterization of the identified clusters as innovation patterns, or innovation strategies, is provided. Furthermore, we examine the correspondence between innovation patterns on the one hand and structural firm characteristics, industry affiliation and impacts of innovation on the other hand. In Section 5, we discuss some methodological issues with respect to the observed weak innovation performance of the service firms and comment upon the convergence of innovation patterns in the manufacturing and service sector. Finally, Section 6 presents the main conclusions and formulates some policy implications.

2. Data: innovation indicators from the CIS-3

The data used in this study are taken from the third *Community Innovation Survey* (CIS-3), conducted in 2001, which covers the firms' innovation activities during the period 1998-2000. The CIS-3 for the region of Flanders is based on a stratified random sample covering 26 industry groups and six firm-size classes.[4] In addition, this study uses firm-level balance sheet data, drawn from the *BEL-FIRST* (2000), a database containing detailed financial information on 335,000 Belgian companies.

Given the purpose of the present study, our analysis is confined to 'innovative firms' only. In the CIS-3, a firm is considered innovative if at least one out of the following four criteria is met: the firm (*i*) has introduced new or significantly improved products (goods or services) on the market; (*ii*) has realized new or significantly improved processes for producing or supplying products (goods or services); (*iii*) was involved in activities – including R&D activities – to develop or introduce on the market new or significantly improved products (goods or services) that are still ongoing (i.e., not completed); or (*iv*) was involved in innovation activities as in (*iii*) but these have been untimely aborted. Applying this definition, 445 firms (66.1%) of the original sample are innovative. From these, 291 firms (65.4%) belong to the manufacturing industry, and 154 firms (34.6%) belong to the service industry. An overview of the distribution of firms in the dataset, by sector as well as by firm size class, is presented in Table A.1 of the Appendix.

In the CIS-3, a multitude of alternative innovation indicators, each highlighting specific facets of innovation, are used to describe the multidimensionality of the firms' innovation performances. In drawing the innovation profiles, we take into account only those indicators that are associated with strategic 'choice' or 'control' variables. Accordingly, variables related to the impacts of the innovation, e.g., increased revenues or market shares, are excluded from the factor analysis and discussed in a later section (see Section 3.1 and Section 4.3). The selected set of indicators represents several aspects of the innovation process; not only are the indictors related to activities aimed at generating new technological knowledge (e.g., R&D), but they also cover many activities related to the adoption and diffusion of technology (e.g., the purchasing of technologically new machinery and equipment, training and marketing activities necessary to introduce innovations, and so on). Based on the CIS-3, we are able to develop a total of 35 innovation indicators[5] that can be summarized as follows:

- *Input indicators*

The traditional input-oriented indicators are mainly related to (1) internal (in-house or intramural) and (2) external (extramural) R&D activities and (3) internal and (4) external R&D expenditures. R&D comprises creative activities, carried out to acquire new knowledge or to use new knowledge for new applications. In general, these investments increase the absorptive capacity of the firms, so that they can benefit more from external information flows.

- *Follow-up-investment indicators*

The input indicators are supplemented by a number of 'non-technological' or 'non-R&D-related' innovation indicators such as: (5) the purchase of special machinery and equipment linked to product and process innovations, including the acquisition of software embedded in new equipment; (6) the acquisition of patents, licenses, trademarks, etc.; (7) innovation-related training of employees connected to the introduction of new products and processes; (8) marketing of innovations (e.g., marketing campaign with respect to the launching of new products); (9) preparations related to methods of delivering new products (i.e., activities aimed at defining procedures, specifications, and operational features), including testing, tooling-up, and trial production, necessary for the introduction of new products and processes; and (10) the total amount of the 'follow-up' investments within these categories as a percentage of sales. Many of these indicators can be associated with the processes of technology adoption and diffusion.

- *Output indicators*

The output-oriented indicators are directly related to the realization of (11) product and (12) process innovation, and (13) patent applications (i.e., EPO and/or USPTO patenting). The patent indicator complements the R&D indicator, in the sense that patenting captures new knowledge created anywhere within a firm and not just within a formal R&D laboratory. The indicator also measures specialization of knowledge creation in fast-growing technologies.

- *Sources-of-information indicators*

Since innovation is systemic – it depends upon complex interactions between many stakeholders – access to relevant information is a critical element of any successful innovation system. Innovation information indicators thus are related to a variety of information sources, ranging from *internal* sources of information ((14) sources within the enterprise itself, or (15) its group of enterprises), over *external* sources of information (market and institutional sources of information, such as (16) suppliers, (17) customers, (18) competitors, (19) universities and schools for higher education and (20) public and non-profit research institutes), to *generally-available* information coming from (21) professional conferences, meetings and journals, and (22) fairs and exhibitions.

- *Innovation-protection indicators*

Successful innovation is not only critically dependent on the capabilities of capturing and managing incoming information flows (i.e., external sources), firms also seek to control the outgoing information flows to the extent that this is possible given the prevailing appropriability conditions. The indicators covering different mechanisms of protection are (23) registration of design patterns, (24) trademarks, (25) copyright, (26) secrecy, (27) complexity of design, and (28) technological lead-time advantages over competitors.

- *Strategic and organizational indicators*

Recently, it has been acknowledged that the innovation strategy is embedded in the broader corporate structure and strategy (e.g., [17]). We therefore incorporate in our analysis some strategic and organizational indicators that are related to (29) changes in corporate strategy, (30) the use of advanced management techniques, (31) changes in the organization structure, (32) the use of new marketing concepts, and (33) changes in product design (including aesthetical changes).

- *Other indicators*

This set of indicators is related to distinctive innovation practices, such as (34) innovation cooperation, which is sometimes considered a ‘throughput’ indicator. Furthermore, we include (35) the occurrence of patents granted in previous years. These patents represent in some way the stock of knowledge available to the firm, and may prove successful (patented) innovation outputs from the past.

3. Methodology and empirical results

In our search for the existence of distinct innovation strategies adopted by firms in the Flemish business sector, we use a two-step, multivariate-analysis procedure. In the first step, we conduct an exploratory *factor analysis* with the aim of reducing the number of variables involved in the CIS-3, while retaining the information that is contained in them. In the second step, we use the extracted factors to identify *clusters* of firms according to their distance and proximity in relation to these factors. Other studies apply a similar approach (e.g., [9,10,19]) yet are confined to either manufacturing or service firms.

Factor analysis

Factor analysis is a relatively effective way of reducing a large number of variables to a smaller set of components or factors. Each factor summarizes the statistical content of all the variables that it includes.

The purpose of the (exploratory) factor analysis is to identify a number of factors, and explain their relationship to the 'raw' CIS-3 data [20, p. 127]. The factors are extracted by using the principal components method. The adequacy of the factor analysis can be assessed by the extent to which the factors are able to reduce the original total variance.

The factor analysis was applied to the set of 35 innovation indicators described above, for a total of 443 observations (two firms were taken out from the analysis due to missing data). As indicated in the previous section, we take into account only those indicators that are associated with strategic 'choice' or 'control' variables. Hence, variables related to the impacts of the innovation are excluded from the factor analysis and discussed in Section 4.3.

The results of the factor analysis are presented in Table 1. From the 35 original CIS-3 variables, ten factors could be extracted that together account for about 57% of the total variance. This result is quite satisfactory, given the large number of indicators involved.[6] The root mean square residual (*RMSR*) is equal to 0.054, which is small, hence implying a good factor solution [21, pp. 106-107]. Besides, an overall value of 0.80 for the Kaiser-Meyer-Olkin (*KMO*) measure of sampling adequacy suggests that the correlation matrix is appropriate for factoring [21, p. 116). At the level of the individual variables, the factor analysis also produces acceptable results. This can be evaluated by using communality and the Measure of Sampling Adequacy (*MSA* equals *KMO* at the level of an individual variable). For 16 indicators the *MSA* measure is higher than 0.80, and only for 5 indicators it is just below 0.70. Half of the communalities (which reflect the amount of variance explained) are higher than 60%, while only 11 indicators have a score below 50%. A lower outcome of communality is probably due to the binary (1, 0) nature of most indicators.

After performing the factor extraction, the obtained solution is usually rotated to increase the interpretability of the factors (e.g., [22]. In the present analysis, the method used for rotation is the Equamax-with-Kaiser normalization. This method attempts to simplify the factor structure matrix by maximizing the variation of factor loadings for both rows (indicators) and columns (factors) (e.g., [23, p. 110]).

Table 1

Cluster analysis

In a second step of the analysis, we conduct a cluster analysis, based on the common factors extracted by the preceding factor analysis. Broadly speaking, cluster analysis is a statistical technique to identify relatively homogeneous groups of observations by taking into account any set of quantitative and qualitative characteristics selected by the analyst. In the present context, the technique consists of grouping the sampled firms, stage by stage, into aggregates or clusters of firms sharing broadly similar characteristics. This is accomplished by minimizing the ‘within-group’ variance and maximizing the ‘between-group’ variance, whilst the number of clusters corresponds to the number of distinctive patterns discernable in the multivariate distribution of the raw data. We used both non-hierarchical (i.e., partitioning, according to the *K*-means method) and hierarchical (i.e., agglomeration, according to Ward’s method) clustering. The non-hierarchical clustering was primarily used for validation purposes.

Based on criteria such as the statistical significance (i.e., reducing the ‘within-cluster’ variance in combination and increasing the R^2), the ‘interpretability’ of the resulting clusters, and the number of firms within each cluster, a seven-cluster solution was finally retained. These seven clusters involve a total of 429 firms (rather than the 443 firms in the original sample); three outliers were taken out beforehand, and a close inspection of the results of initial runs of the clustering procedure revealed that 11 firms (or 2.5% of the sampled firms) have some extreme, unrealistic scores on certain innovation indicators and, consequently, they do not fit into any one of the seven identified clusters. The assignment of the firms to the various clusters is ‘mutually exclusive’ (i.e., no firm is assigned to more than one cluster), and ‘collectively exhaustive’ (i.e., all 429 firms are assigned to one of the identified clusters).

The approximate R^2 is equal to 0.34, which indicates an acceptable fit of the model to the data. In addition, the identified clusters are significantly dissimilar in terms of the configurations of innovation indicators.

A more elaborate discussion of the results of the cluster analysis and a characterization of the clusters as patterns of innovation is provided in the next section.

4. Characterizing clusters as patterns of innovation

Through the cluster procedure, the firms are sorted into seven groups according to their similarity and proximity along the extracted factors. Given the underlying principle of the method applied, we can use the particular configurations of innovation indicators to characterize the ‘idiosyncratic’ innovation behavior of groups of firms. In other words, we interpret the seven identified clusters as particular patterns of innovation, or innovation strategies, based on the apparent similarity of the constituent firms in terms of their scores on the various innovation-related, technological and non-technological indicators.

Analysis of the relative scores of the identified clusters on the ten underlying factors, allows to distinguish between the following patterns of innovation: (*i*) science-based innovators (CL1); (*ii*) development-based innovators (CL2); (*iii*) resource-based innovators (CL3); (*iv*) market-oriented innovators (CL4); (*v*) research-based innovators (CL5); (*vi*) service-oriented innovators (CL6), and (*vii*) cost-oriented innovators (CL7). An overview of the relative factor scores of the identified patterns of innovation is presented in Table 2.

Table 2

From this table, the following key findings emerge. First, a comparison of the relative factor scores reveals large differences between the clusters. Therefore, a distinction can be made between 'high-profile' innovators (*CL*2 and *CL*5), 'medium-profile' innovators (*CL*1 and *CL*3), and 'low-profile' innovators (*CL*4, *CL*6, and *CL*7).[7] The high- and medium-profile (development-, research-, and science-based) innovators exhibit high scores on one or more factors, have a high perceived innovation risk, apply frequently internal and external sources of knowledge (e.g., R&D activities and technological cooperation) and try to protect the benefits of their innovation efforts by various strategic and formal innovation-protection methods and patents/patent applications. The low- and medium-profile (resource-based, market-oriented, cost-oriented and services) innovators on the other hand, generally score low on various factors and have a low perceived innovation risk. They often rely on external technology sources (e.g., suppliers). These innovators can alternatively be designated as 'incremental innovators' or 'innovation adopters'. To the extent that they use internal sources, these are primarily oriented towards (non-technological) strategic and organizational changes as well as towards the training of their staff to raise the firm's absorptive capacity and improve its innovation capabilities.

Furthermore, when comparing the cluster solution to the taxonomic model as developed by Pavitt [4], we can conclude the following. Firms belonging to the high- and medium-profile clusters seem to fit into Pavitt's category of 'knowledge-based firms'. These firms usually try to seek a balance between product and process innovation, where process technologies are mainly sourced from suppliers, and product technologies are extended internally and/or sourced from universities or research institutes (with limited collaboration with customers or competitors). In addition, the firms in the low- and medium-profile, resource-based clusters seem to fit into Pavitt's categories of 'supplier-dominated firms' or 'production-intensive firms'. In general, in particular the relative focus of the firms from the low-profile clusters is aimed at product or at process innovation. They rely heavily on suppliers as the source of new or improved process technologies (with a limited role of customers as a source of information) or customers as the 'drivers' of new or improved products (with a limited role of suppliers).

To conclude, a detailed characterization of the identified clusters based on their scores on the innovation indicators applied, is presented in Table 3.

Table 3

Correspondence between innovation patterns and firm characteristics

Analyzing the relationship between innovation and structural firm characteristics or firms' economic performances (e.g., increased profitability or greater levels of labor productivity) is extremely important from a policy point of view. To gain some insights into this relationship, we combined the CIS-3 data with some other firm-specific information, taken from *BEL-FIRST* (2000) containing 300 000 annual accounts of Belgian companies.

Inferences regarding productivity and competitiveness of the business sector are usually based on rankings by the standard industrial classification. Alternatively, one may assess the homogeneity of the innovation strategies, rather than industries, in terms of structural firm characteristics and economic performances (i.e., the 'homogeneity hypothesis'). A natural approach is to test whether significant differences exist between innovation strategies with respect to the average firm characteristics and economic performances. A negative outcome would support the 'heterogeneity hypothesis', according to which more than one innovation strategy is (at least temporarily) economically feasible [10].

To evaluate the homogeneity versus heterogeneity proposition, we consider the following indicators that are generally used to describe the structural characteristics of firms[8]: (*i*) firm size, measured by the number of employees; (*ii*) corporate group membership; (*iii*) human capital intensity (labor quality), measured as the share of highly qualified (educated) employees in total employment; and (*iv*) physical capital intensity or capital-labor ratio, measured as total nominal investments in tangible assets per employee (×1,000). In addition, we consider the following measures of firms' economic performances: (*v*) nominal labor productivity, measured as gross value added per employee (×1,000); and (*vi*) export intensity, measured as the share of exports in total sales. However, it should be noted at this point, testing the economic performances associated with each innovation pattern within a cross-sectional framework is a difficult task, since one would expect a certain time lag before the impacts of innovation activities in terms of economic performances would effectively materialize. Therefore, our test implicitly assumes medium-term persistence of innovation strategies (i.e., no structural change in the short run).[9] An overview of the firm characteristics and economic performances by cluster is provided in Table 4.

Table 4

It is shown that the average firm size of the high-profile innovators is relatively large. This may not surprise, since in particular large firms often use a broad scale of innovation-inputs, sources of information and innovation protection methods. In addition, it is shown that the average firm size of the low-profile innovators, that apply only a limited set of innovation-inputs, is the smallest. Furthermore, export intensity ranges from 29% for firms in the market-oriented and service-oriented innovation clusters (*CL*4 and *CL*6, respectively) to 64% for firms in the research-based innovation cluster (*CL*5). Labor productivity varies only moderately across innovation strategies, with an exception for the research-based innovators (*CL*5). Regarding labor productivity, taking the figures as such may be misleading. Specifically, one has to correct at least for (*i*) firm size (*CL*5 contains the highest share of large firms), and (*ii*) capital intensity (*CL*5 shows the highest physical capital intensity) of the firms in the sample. In other words, firms' performance in terms of labor productivity is determined not only by the variable 'innovation pattern', but also (and probably to an even larger extent) by some other variables.

An examination of these results from a cluster perspective shows that the research-based innovation cluster (*CL*5) stands out with high scores on all of the investigated indicators. Relatively low scores on the other hand are to be noted for firms in the market- and service-oriented innovation clusters (*CL*4 and *CL*6, respectively). The results found for firms in the service-oriented cluster (*CL*6) seem to confirm some of the 'stylized facts' and international trends of service firms as described in the literature. The service innovators are relatively small and have both a low capital-labor ratio and export intensity. On the other hand the high score on human capital intensity confirms the importance of the people-factor that is generally attributed to service firms.

Correspondence between industry affiliation and patterns of innovation

Inferences with respect to firms' innovation profiles are often based on sectoral classifications that use standard industry classification codes. However, any such analysis makes sense only if the industries are sufficiently *homogeneous* in terms of the constituent firms' innovative behavior. While the heterogeneous nature of innovation is widely recognized in the literature, this heterogeneity has often been neglected in empirical research since in many studies only broad industry aggregates are applied. However, if innovation strategies are not specific to industries, and if firms from a given industry apply different types of innovation strategies, the homogeneity assumption is not valid. In addition, if firms from manufacturing and services sectors apply similar innovation strategies, a dichotomous approach to study innovation might not be appropriate.

To test the correspondence between industries and innovation patterns in the Flemish business sector, we distinguish 16 industries, mostly at the 2-digit NACE-level.[10] The industries include both manufacturing (11 sub-sectors) and services (5 sub-sectors). The manufacturing industries considered are: 'Textiles' (TEXTL), 'Wood & Paper' (WO&PA), 'Printing & Publishing' (PR&PU), 'Chemicals & Pharmaceuticals' (CH&PH), 'Metals' (METAL), 'Machinery & Other equipment' (MACH), 'Rubber & Plastics' (RU&PL), 'Electronics & Electro-mechanics' (ELECTR), 'Food & Beverages' (FO&BE), 'Motor vehicles & Other transport equipment' (TRANS), and 'Other manufacturing' (OTH.IND). The service industries include: 'Wholesale A' (WHOLE-A) (e.g., wholesale of agricultural products, intermediary products, food and beverages, household goods, and the like), 'Wholesale B' (WHOLE-B) (e.g., wholesale of machinery and other equipment, and 'other wholesale'), 'Other material services' (MAT.SV) (i.e., mainly transport-related services), 'Computer & related activities' (COMPU), and 'Other immaterial services' (IMMAT.SV). The composition of these industries over the sampled firms is presented in the Appendix, Table A.1.

Firstly, the joint distribution[11] of the firms' innovation strategies and their industry affiliations suggests an overall low correspondence between the two dimensions. Although the *Chi*-square test of statistical independence seems to be (weakly) supporting the 'homogeneity hypothesis', a closer inspection of the results reveals that the joint probabilities are significant in only a few instances. In other words, only a few industries appear to be more (less) representative for a particular innovation strategy than others, and *vice versa*. The low correspondence between industry affiliation and pattern of innovation should not be surprising, though, since firms have only been assigned to one (primary) NACE code (i.e., the most relevant), yet firms may actually carry out other (secondary) business activities as well. This, in turn, may explain the co-existence of different innovation strategies within a particular industry.

Secondly, it is more instructive to look at the conditional distribution. The conditional distributions of the industries, by innovation strategies, are visually shown by the radar charts in Figure 3. From these radar-charts we can assess the *heterogeneity* of the identified innovation clusters in terms of their industry composition. In addition, we calculated simple Herfindahl Indexes[12] (HI), which indicate that the group of cost-oriented innovators (*CL*7) turns out to be the most heterogeneous in terms of industry composition (HI = 0.076, see panel G of Figure 3), whereas the group of development-based innovators (*CL*2) is the most homogeneous (HI = 0.110). It contains mainly firms from the ELECTR and CH&PH industries.

Along similar lines, the *diversity* of the various industries in terms of the constituent firms' innovation strategies is shown in Figure 4, based on the conditional distributions, by industry. The values of the corresponding Herfindahl Indexes reveal that the firms affiliated with the CH&PH and IMMAT.SV industries are the most diverse with respect to their innovation strategies (see panels D and P of Figure 4), whereas firms that belong to the WO&PA and PR&PU industries are the least diverse (see panels B and C of Figure 4, respectively).

From these results we can safely conclude that firms are comparatively free in choosing a particular innovation strategy, even under broadly similar (sector-specific) economic and/or technological conditions. Evidently, this conclusion is not in line with Pavitt's 'sectoral determinism'.

Additionally, it is revealed that service firms 'cluster together' in the weakly performing service-oriented innovation cluster (*CL*6). Essentially, this was also the reason why we designated this cluster as a group of (low-profile) 'service-oriented innovators'. The service firms in this cluster mainly belong to the COMPU, WHOLE-A, and IMMAT.SV industries (see panel F of Figure 3 and panels L, O and P of Figure 4).

The analysis of the various innovation clusters, along with their industry composition, produces some mixed results. On the one hand, the clustering of service firms in the 'service-oriented innovation cluster' (*CL*6) supports the view that the type of innovation activities found in manufacturing firms is markedly different from the one in service firms. Only the MAT.SV industry (which mainly groups firms operating in the field of transports and logistics) as well as the WHOLE-B industry seem to dissociate themselves from this cluster by choosing (another) low-profile innovation strategy. On the other hand, Figures 3 and 4 provide strong evidence against a strict 'sectoral determinism', as no single innovation strategy can be linked exclusively to a particular manufacturing or service industry. The co-occurrence of both manufacturing and service firms within a single cluster – implying that they choose a similar innovation strategy – is not so much of a surprise. It may be an expression of the observation that, to an ever increasing extent, manufacturing firms' product innovations are accompanied by (new) additional services [25]. This increased 'service-content' of manufactured products (i.e., the supply of physical products along with supporting services, which are combined into a single 'package') should somehow be mirrored by the type of innovation activities deployed by the manufacturing firms [26].

Correspondence between innovation patterns and impacts of innovation

In general, product innovations are expected to be positively associated with R&D [27] and patent activity [28]. The relationship between product innovation and the scale and complexity of process technology, as reflected by the capital-labor ratio and average firm size, is less clear-cut, however. Furthermore, one would generally expect a relatively high proportion of resources to be devoted to process innovations in production-intensive firms that are characterized by a high physical capital intensity, large firm size, and industrial concentration [4]. These expectations seem to be confirmed by our empirical findings in Table 5.[13]

The impacts of product and process innovations appear to be prominent for the firms in the research-based innovation cluster (*CL*5). Other important intentions of their innovations are: improving environmental, health, and safety aspects and/or reaching enhanced compliance with governmental regulations, norms, and standards. On the other hand, the innovation activities of firms in the development-based innovation cluster (*CL*2) are mainly directed towards product innovations that are particularly aimed at opening-up new markets. The firms in the clusters of resource-based and cost-oriented innovators (*CL*3 and *CL*7, respectively) are heavily involved in process innovations aimed at increasing their internal production flexibility and/or expanding the production capacity.

Furthermore, reducing labor and other (material and energy) costs per unit of production is also an important aspect of the process innovations for firms included in the development-based and cost-oriented innovation clusters (*CL*2 and CL7, respectively). Process innovations are expected to be most important for firms belonging to the TEXTL, WO&PA, FO&BE, METAL, and TRANS industries. Many firms in these industries are characterized by continuous-process technology and/or assembly operations. Also, process innovations seem to be very important for the firms in the research-based innovation cluster (*CL*5) belonging to the CH&PH and ELECTR industries.

Finally, the empirical results show that the firms in the service-oriented innovation cluster (*CL*6) exhibit very low scores on (almost) all the impacts considered. This finding is quite surprising, because it does not support the general view that improving the quality of the services offered as well as extending the service range and/or opening-up new markets are important targets of innovation activities of service firms [25]. Yet, also in previous editions of the CIS, a similar finding was reported (e.g., [29]). In the next section, we provide some more detailed comments on these findings.

Table 5

5. Innovation in manufacturing and service firms

In the next sections, we discuss to what extent the 'stylized facts' about innovative behavior of service firms reported in the literature are echoed by the results of the present analysis. Subsequently, we comment upon the most important results of our 'integrative' approach of studying the innovation behavior of service and manufacturing firms within a single analytical framework and whether the traditional 'dichotomous approach' to study both business sectors is justifiable.

Service firms: weak innovators? A methodological note

Service firms are generally considered to be less innovative than manufacturing firms, and to be different in terms of inputs, outputs, and impacts of innovation (e.g., [30,31] Sirilli). The lower innovation rate of service firms is confirmed in Table A.1 of the Appendix since 72.7% of the manufacturing firms in our sample are innovative, compared to 56.4% of the service firms. In addition, the lower innovativeness of service firms is also confirmed by the results of the present factor and cluster analysis. Focusing on the sample of innovative firms, it appears that the service firms are 'over-represented' in a separate cluster, which has been characterized as a group of low-profile innovators that score low on most of the selected innovation indicators.

The observed weak innovation performance of service firms, however, may reveal some weaknesses of measuring innovation in service firms. Until recently, innovation in services has received little attention, so we know much less about innovation in services than in manufacturing. This implies that we just begin to understand the innovation process in service firms. In interpreting the present results, it has to be taken into account that the empirical findings with respect to service firms' innovation performance may be somewhat contentious and ambiguous for various reasons.

Firstly, there is still some ambiguity as to what constitutes 'innovation' in the service sector, and hence, differences in interpretation are likely to affect the outcomes of many innovation surveys (i.e., the meaning assigned to 'innovation' by the survey respondents may vary in ways that are still poorly understood). With reference to the CIS, [15] point out that the distinction between product and process innovation is justifiable for manufacturing, but this might not be the case for services. Stated differently, the 'assimilation approach' [2], which is used in the CIS and which considers innovation in service and manufacturing firms as being (highly) similar – and hence uses the same concepts and indictors for firms from both sectors – might have led to problems of misinterpretation for respondents from service firms, leading to 'incorrect' answers to some of the survey questions.

Secondly, [32], among others, distinguish several features that are specific to production and innovation in services: (*i*) the close interaction between production and consumption of services (i.e., 'co-terminality'); (*ii*) the increasing information content of services; (*iii*) the important (and growing) role played by human resources in service production, and (*iv*) the importance of organizational change as a means of producing and delivering (new) services. This characterization implies that 'non-technological' innovations, rather than, say, high-tech, R&D-based innovations, are an important dimension of innovative firms in the service industry (see also [33,34]). Precisely several 'non-technological' aspects of innovation in services may not have been adequately or sufficiently accounted for by the CIS-3 (see also [32]). Therefore, one may ask whether the results are not, at least partly, an artifact of the particular set-up and 'technology' orientation of the CIS-3, that still focuses (too much) on manufacturing firms and, for that reason, systematically underestimates innovation activity in the service sector.

In this respect, we want to point at a notable result that shows up when studying in more depth the realization of product innovation – which encompasses both goods and services in the CIS-3 – and process innovation of the different clusters (Table 6). With respect to the service-oriented cluster, it is remarkable that the high score on product innovation is not translated in high scores on product oriented impacts on innovation (see Table 5). In this respect, the Flemish CIS is no exception, since large differences between the scores on product and process innovation for the service-oriented cluster coincide with the results found by [15].

Table 6

Thirdly, describing and measuring innovation in services is far more complicated than in manufacturing, since service innovations tend to be of an extremely heterogeneous nature and innovation in this sector often coincides with new patterns of product distribution or client interaction [35]. Acknowledging the specificities of the dataset used, these first results demonstrate that several aspects of innovation in services, such as the increased blurred distinction between products and services (which makes it difficult to figure out whether companies are selling a product with a service or a service with a product), may not have been adequately or sufficiently accounted for by the CIS-3. This may explain, at least partially, the low innovation performance of service firms. In this respect, we welcome the current revisions of the Oslo manual on innovation, in which a broader definition of innovation is used that includes marketing and organizational innovation and recognizes the importance of linkages in the innovation process.

Are manufacturing and services converging?

In the present paper, firms from both the manufacturing and service sector are treated 'on an equal footing' and integrated into a single analytical framework in order to investigate the variation in the content and nature of the innovation processes of firms across and within both business sectors.

From this analysis, it appears that service firms' innovative behavior is markedly different from that of manufacturing firms. Based on our results, many service firms seem to be adopting a distinctive innovation pattern and to perform only weakly on the selected innovation indicators, compared to manufacturing firms.

In addition, it is revealed that there exists no strict association between industry affiliation and innovation-cluster membership of the firms in the Flemish business sector. In other words, we found no compelling evidence of a clear-cut sectoral characterization of strategies of innovation. In addition, our results highlighted the co-existence of different innovation strategies within the same industry, which means that there are important ‘degrees of freedom’ with respect to innovation strategies adopted by firms.

These findings raise some doubts about the ‘sectoral determinism’ suggested by Pavitt [4], and are fully in line with the findings of [6], among others. On the other hand, we detected weak indications of correspondence between the choice of innovation strategy and industry affiliation. Some industries were found to be more representative for particular strategies of innovation than others, which means that some firms in these industries are to some extent constrained in their choices as to the orientation of the innovation activities and the type of innovations to produce. Consequently, we stand somewhere midway in the on-going debate between the ‘sectoral-determinism’ and ‘strategic-choice’ perspectives.

These seemingly ambiguous findings are in line with the empirical results found by [36], when answering the question whether service firms innovate differently from manufacturing firms. His results indicated that the answer to this question is both ‘yes’ and ‘no’ [36, 2005, p. 24]. The apparent ambiguity stems from the fact that, although a separate manufacturing mode of innovation or a separate service mode of innovation is non-existent, differences exist in the innovation orientation between manufacturing and service firms and the prevalence of specific innovation strategies among specific service versus manufacturing sectors (i.e., some service firms' innovation strategies exhibit traits that are commonly found among manufacturing firms, and vice versa).

In this respect, we state that it is important to realize that firms rarely innovate alone; they do so mostly within the context of structured relations with other firms, institutional infrastructures, networks, formal knowledge-creating institutions (such as universities or research centers), legal and regulatory systems, and so on. Accordingly, there is an apparent need for a *system-based* approach of knowledge creation and innovation. Hence, the appropriate unit of analysis may not be the firm but rather the *network* of firms or the entire *value chain*.

The present study, like most other innovation studies, uses the standard industrial classification of firms to characterize their (choices of) innovation strategies. However, using a standard industrial classification creates several problems if one wants to analyze innovation in productive and competitive chains, industrial districts, regional clusters, or networks.[14] In which sectors do innovations originate and in which are they further developed? How does one measure the synergies created within clusters, networks and industrial districts? How is innovation diffused among the participating firms? R&D outsourcing, distributed models of innovation (e.g., for large multinational enterprises), networks of firms that collaborate or compete, rather than individual firms, are becoming more common (e.g., [37,38]). Also, many service firms seem to possess favorable preconditions for co-operative arrangements with research institutions [29]. Given the high qualification of their workforce, software companies and consulting engineers, for example, may be less affected by important barriers to co-operation with bodies from the public-sector infrastructure (e.g., unfamiliarity with the idiosyncrasies and customs of universities and academic communities). Many service firms are also particularly suited to act as a driving force to enhance the relationships between public-sector research institutions and small and medium-sized enterprises in the manufacturing sector. Consequently, many service firms may play an important role as information mediators, which make them central to the diffusion and creative use of new technologies.

In order to account for this type of innovative interactions between firms, surveys should gather more information about the 'linkage capabilities' that firms possess in order to be part of an innovation network. Precisely these linkage capabilities refer to the ability of a firm to establish collaborative and co-operative relationships with other agents, and are key to its competitive and technological performance [15]. The CIS-3 only partly accounts for such collaborative innovation, asking about whom (the firm alone) or with who technology-based product and process innovations were introduced, the relative importance of the various innovation partners, and their location. Unfortunately though, in our attempt to integrate this type of information into the analysis, several data deficiencies could be detected.

Although from a statistical point of view, it is extremely difficult to adopt a different unit of analysis, we believe that a possible avenue for future research is to define so-called 'regional firms' or 'localized firms'; that is, to use a classification of firms based on (*i*) geographical location or proximity, and (*ii*) economic (input-output) linkages – provided that sufficient micro-level data are available. However, at the same time it is to be expected that carrying out analyses based on such data will very likely be hampered by several factors, including confidentiality requirements.

6. Conclusions and policy implications

The analysis of the CIS-3 data has greatly expanded our understanding of the many different strategic orientations and practices that may be adopted by innovative firms in the Flemish business sector, including both manufacturing and services. Specifically, the analysis allowed us to arrive at a preliminary clustering of Flemish firms, based on similarities with respect to their 'innovation strategy' and related practices.

The empirical results in this study indicate that Flemish firms are particularly heterogeneous with respect to their innovative behavior. By applying factor and cluster analysis to the CIS-3 data, a set of seven analytical clusters is identified that exhibits clearly distinctive configurations of innovation-related indicators. Each of the clusters can be interpreted as a group of firms with a distinctive pattern or strategy of innovation.

The relatively large number of categories that is necessary to capture the complex phenomenon of innovation in the Flemish business sector seems to suggest that Pavitt's [4] classification into three or four strategies of innovation may in fact be too narrow for this purpose. This finding is very likely to be due to the fact that our analysis is based on firm-level data compared to sector-level data and that it covers a much broader range of innovation indicators.

Our results indicated that there is no strict association between industry affiliation and innovation-cluster membership of the firms in the Flemish business sector. In other words, we found no compelling evidence of a clear-cut sectoral characterization of strategies of innovation. In addition, our results highlighted the co-existence of different innovation strategies within the same industry, which means that there are important 'degrees of freedom' with respect to innovation strategies adopted by firms. These findings raise some doubts about the 'sectoral determinism' suggested by [4]Pavitt, and are fully in line with the findings of [6], among others. On the other hand, we detected weak indications of correspondence between choice of innovation strategy and industry affiliation. Some industries were found to be more representative for particular strategies of innovation than others, which means that some firms in these industries are to some extent constrained in their choices as to the orientation of the innovation activities and the type of innovations to produce. Consequently, we stand somewhere midway in the on-going debate between the 'sectoral-determinism' and 'strategic-choice' perspectives.

In addition, the present analysis indicated that service firms' innovative behavior is markedly different from that of manufacturing firms. Many service firms seem to be adopting a distinctive innovation pattern and to perform only weakly on the selected innovation indicators, compared to manufacturing firms. The observed weak performance of service firms, however, may reveal some weaknesses of the CIS-3 as well. Acknowledging the specificities of the dataset used, these first results demonstrate that several aspects of innovation in services, such as the increased blurred distinction between products and services, and a potential bias towards technological innovations, may not have been adequately or sufficiently accounted for by the CIS-3 and, therefore, may have resulted into an underestimation of innovation activity in the service sector. In this respect, we welcome the current revisions of the Oslo manual on innovation, in which a broader definition of innovation is used that includes marketing and organizational innovation and recognizes the importance of linkages in the innovation process.

Finally, the results of this analysis have a number of important implications for innovation policy development. Firstly, since great diversity exists in the innovative behavior of firms, caution is warranted for the application and interpretation of innovation statistics that are based on general broad (sectoral) classifications. Secondly, when drafting innovation measures, policy makers need to take into account this great diversity in innovation strategies. Thirdly, the weak association between innovation strategies and sector affiliation implies that tailoring innovation policies to broadly defined sector aggregates (e.g., high-technology versus low-technology sectors), runs the risk of being inefficient since multiple strategic innovation orientations and practices seem to exist within a single industry. This finding implies the necessity of further differentiation in policy design and the need for 'accommodative' policy measures. Policy makers should develop a varied and flexible portfolio of policy measures that allows being tailored to the specific needs of (a group of) companies with a particular innovation strategy. These considerations on public policy are, of course, incomplete. The development of more specific recommendations would require not only a more thorough development of the analysis we have presented here, but also an extension of it. In addition to strategy, we would also have to consider, for example, complementarities and patterns of interdependency, both within and among sectors.

Footnotes

[1] Do we look at innovations as technological objects, or at the innovation process? Do we look at significant innovations, or at the firms that produce them? Which dimensions of innovation do we explore? How do we classify "newness" and degrees of innovation? (Is it new to the firm, the market, the world? Is it incremental or radical innovation?) What kind of measurement concept is chosen? What are the measurement units?

[2] [7] also used a statistical procedure to classify firms based on several innovation indicators and knowledge sources, but they refrained from combining the two types of information in a systematic way. In addition, their empirical work is based on information from the 500 largest European firms and, therefore, their results are representative of only a specific portion of the economy.

[3] The set-up and orientation of CIS in general, and CIS-3 in particular, is heavily debated in the recent literature (e.g., [15]).

[4] In the Flemish CIS-3 a "mixed-mode" data collection method was applied (i.e., MAIL and CAPI). In the present study, we use the MAIL-data since only these data have been "awarded" an official status in the OECD context for reasons of international methodological comparability.

[5] Most of the input- and output-oriented indicators, as well as the indicators related to follow-up investments and protective measures, are defined as yes/no or [1,0] binary variables. The main advantage of a binary indicator is that it is based on a simple yes or no question. However, such an indicator does not measure the intensity of the innovation activity; it simply indicates that some innovation-related activity took place. The variables pertaining to the use of innovation-related information are ordinal, with 5 response levels (measured on a five-point Likert scale), ranging from "very low" (value = 1) to "very high" (value = 5). The only quantitative variables are those related to internal and external R&D investments (expenditures), and the total amount of follow-up investments (as a percentage of sales).

[6] Moreover, the stability of the results from the factor analysis was confirmed by performing supplementary comparative analysis of the data using the computer package Mplus 2.13, which is particularly suited for binary and categorical data. Model results are available from the authors upon simple request.

[7] We prefer to use the terms "high-profile", "medium-profile", and "low-profile", rather than the standard terms "high-tech", "medium-tech", and "low-tech" – terms that are based on the standard OECD classification, in which *industries* are distinguished in terms of *average* R&D intensities.

[8] These structural firm characteristics or economic performances are not necessarily related to the 1998-2000 innovation activities. The results are reported solely for illustrative purposes.

[9] In their empirical analysis of the relation between innovation and performance, [24] found a reasonably high level of persistence in innovative activities.

[10] It can be expected that the level of sector aggregation is negatively related to the degree of homogeneity of the firms within the chosen sectors. The number of industries was determined considering the nature of the activities within the sectors (i.e., sufficiently homogeneous), and taking into account the number of firms within each sector.

[11] Not reported here due to space limitations.

[12] The Herfindahl Index for each cluster j is defined as $HI_j = \sum_{i=1}^{n} S_{ij}^2$, where S_{ij} signifies the share or column-wise conditional probability of industry group i associated with cluster j. A HI below 0.1 indicates an unconcentrated index. A HI between 0.1 to 0.18 indicates moderate concentration.

[13] The results in Table 5 are based on the calculated positive or negative (standardized) "distance" between the vector of mean values for each cluster and the corresponding mean vector for the whole sample of firms.

[14] The term "cluster" as used in the present study should be clearly distinguished from clusters as firms/industries that are closely linked in an economic sense or as localized networks.

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Table 1 Identified factors

Factors	Percentage of variance explained (cumulative %)	Correlation coefficients
(A) Factor 1: Strategic innovation protection	7.0% (7.0%)	
[28] Technological lead-time advantage over competitors		0.770
[26] Secrecy		0.765
[27] Complexity of designs/design process		0.757
[1] Internal R&D activities		0.403
(B) Factor 2: Market and institutional information/technology	6.9% (13.9%)	
[22] Fairs and exhibitions		0.785
[21] Professional conferences, meetings and journals		0.730
[20] Non-profit research institutes		0.583
[18] Competitors		0.525
[19] Universities and schools for higher education		0.489
(C) Factor 3: Strategic and organizational changes	6.5% (20.4%)	
[29] Implementation of new corporate strategic orientations		0.778
[31] Implementation of new organizational structures		0.755
[30] Implementation of new management techniques		0.744
[32] Introduction of new marketing concepts or strategies		0.616
(A) Factor 4: Patents and patent applications	6.1% (26.5%)	
[35] Patents granted		0.845
[13] Patent applications		0.825
(A) Factor 5: Formal innovation protection	5.9% (32.4%)	
[23] Registration of design patterns		0.747
[24] Trademarks		0.730
[25] Copyrights		0.690
[33] Aesthetical changes		0.371
(C) Factor 6: R&D expenditures and cooperation	5.7% (38.1%)	
[4] External R&D expenditures as a percentage of sales		0.808
[2] External R&D activities		0.589
[3] Internal R&D expenditures as a percentage of sales		0.557
[34] Innovation-related cooperation		0.381
(C) Factor 7: Follow-up investments using internal sources	5.4% (43.5%)	
[8] Market introduction of innovations		0.701
[9] Preparations related to methods of delivering new products		0.618
[7] Innovation-related training of employees		0.444
[11] Product innovation		0.437
(B) Factor 8: Internal and user-related information/technology	4.8% (48.3%)	
[15] Information supplied by other firms within the group		0.603
[17] Information from down-stream interactions with clients and customers		0.532
[14] In-house information, mainly drawn from the own production and delivery departments		0.414
(B) Factor 9: Supplier-related information/technology	4.5% (52.8%)	
[12] Process innovation		0.743
[5] Acquisition of special machinery and equipment		0.583
[16] Information from up-stream interactions with suppliers		0.291
(C) Factor 10: Follow-up investments using external sources	3.9% (56.7%)	
[10] Follow-up investments as a percentage of sales		0.670
[6] Acquisition of other external knowledge		0.507
Number of observations	443	
Kaiser-Meyer-Olkin measure of sampling adequacy	0.795	
Root mean square off-diagonal residuals (RMSE)	0.054	

Table 2 Factor intensities, by cluster

Clusters (number of firms)	Factors										Profile
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	
CL1. Science-based innovators (58)	+	+++	–	–	––	–	+	–––	○	–	Medium
CL2. Development-based innovators (37)	+++	+	+++	+	+++	+++	++	+	++	+++	High
CL3. Resource-based innovators (51)	+	–	++	–	+	○	+++	+	+++	+	Medium
CL4. Market-oriented innovators (75)	–––	+	+	––	–	–––	––	++	+	––	Low
CL5. Research-based innovators (51)	++	++	+++	+++	++	+++	++	+++	+++	++	High
CL6. Service-oriented innovators (75)	––	––	–––	–	–	––	○	––	–––	–––	Low
CL7. Cost-oriented innovators (82)	○	–––	––	–––	–––	–	–––	–	++	○	Low

Note: The symbols '**+++**', '++', and '+' denote very high, high, and just above average, respectively, while '–––', '––', and '–' denote very low, low, and just below average, respectively. The symbol '○' indicates average factor intensity.

Table 3 Characterization of clusters

Clusters (innovation paterns)	Description
CL1. Medium-profile **science-based** innovators	▪ Rely heavily on various sources of information. ▪ They are aware of the value of information and implement several strategic innovation protection methods.
CL2. High-profile **development-based** innovators	▪ Private intramural (in-house) and extramural R&D activities, R&D cooperation. ▪ Often have an R&D laboratory at their disposition. ▪ Emphasis of the R&D expenditures is on ‘D’ rather than on ‘R’. ▪ Specificity/complexity of innovation. ▪ Protect their innovation by various formal innovation protection methods.
CL3. Medium-profile **resource-based** innovators	▪ Weak R&D performers. ▪ Spend proportionally more on follow-up investments such as ‘buying-in’ new technologies from suppliers and preparations for the introduction of new or improved products, and the marketing of their innovations. ▪ Often directed to realizing process innovations. ▪ Strongly focused on training and the introduction of new organizational structures.
CL4. Low-profile **market-oriented** innovators	▪ Score high on freely accessible sources of information as well as market-oriented sources of information and information from other firms within the group. ▪ Benefit mainly from a wide and diversified (informal) network that spans the entire value chain. ▪ Invest a considerable amount of money into the introduction of new organizational structures to facilitate innovation.
CL5. High-profile **research-based** innovators	▪ Heavily involved in R&D activities, the use of scientific knowledge, and other innovation activities. ▪ They actively pursue innovation, since they score manifestly high on all of the identified factors. ▪ R&D-activities are mainly devoted to generating new scientific/technological knowledge. ▪ Use of patents to protect innovation against imitation.
CL6. Low-profile **service-oriented** innovators	▪ Mainly service firms. ▪ Perform weakly in terms of all innovative activities, except for the important efforts devoted to the market introduction of product innovations. ▪ Product innovations are mainly to be seen as new procedures for providing services to their clients.
CL7. Low-profile **cost-oriented** innovators	▪ Aim at realizing process innovation to reducing costs per unit of production and/or to expand production capacity. ▪ Price competition, low appropriability, and little innovation opportunities (weak innovation performance). ▪ External knowledge is usually confined to suppliers of machinery and equipment, weak links with users.

Table 4 Structural firm characteristics and performances, by cluster (innovation patterns)

Structural firm characteristics and performances	Clusters (innovation patterns)						
	Science-based	Development-based	Resource-based	Market-oriented	Research-based	Service-oriented	Cost-oriented
Firm size	136	426	249	100	596	137	229
Corporate group	0.66	0.80	0.63	0.51	0.86	0.45	0.56
Human capital intensity	0.27	0.26	0.25	0.19	0.34	0.29	0.17
Physical capital intensity	0.4	0.6	0.5	0.5	0.6	0.3	1.8
Labor productivity	2.7	2.8	2.6	2.3	3.7	2.6	2.5
Export intensity	0.56	0.44	0.53	0.29	0.64	0.29	0.38

Table 5 Impacts of innovation by cluster (innovation patterns)

	Clusters (innovation patterns)						
	Science-based	Development-based	Resourc e- based	Market-oriented	Research - based	Service-oriented	Cost-oriented
Product oriented impacts	–	++	○	+	+++	––	–––
Extending product/service range	–	++	–––	+	+++	○	––
Opening-up new markets	–	+++	+	–	++	––	–––
Improved product/service quality	–	+	○	++	+++	–––	––
Process oriented impacts	○	○	++	○	+++	–––	+
Increasing production flexibility	+	++	+++	○	+	–––	++
Expanding production capacity	○	+	+++	+	○	–––	++
Reducing labor costs	–	++	–	+	+++	–––	+
Reducing other input costs	○	○	–	++	+++	–––	+
Other impacts	++	+	––		+++	–––	–
Improving environmental, health, safety	++	+	–	+	+++	–––	○
Improving compliance with regulations	++	+	––	+	+++	–––	–

Note: The symbols '+++', '++', and '+' denote very high, high, and just above average, respectively, while '–––', '––', and '–' denote very low, low, and just below average, respectively. The symbol '○' indicates average impact.

Table 6 Type of innovation output, by cluster (innovation pattern)

Type of innovation	Clusters (innovation patterns)						
	Science-based	Development-based	Resource-based	Market-oriented	Research-based	Service-oriented	Cost-oriented
Product innovation	74%	100%	94%	83%	92%	96%	35%
Process innovation	71%	81%	96%	69%	84%	19%	95%

Figure 1 Different forms of classification

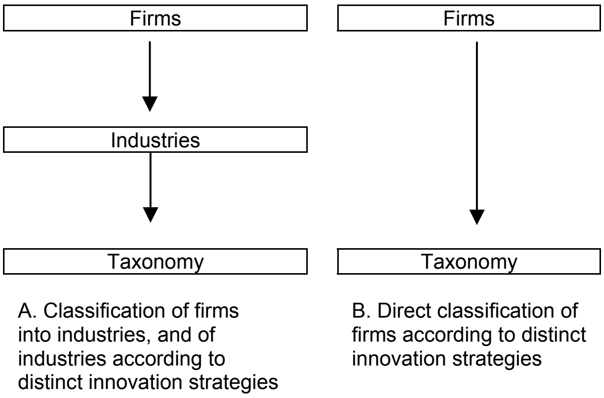


Figure 2 Shift in research focus from manufacturing to services

Manufacturing

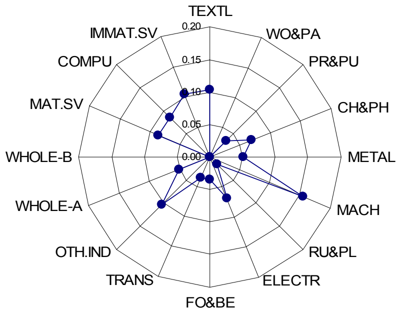
Pavitt (1984) [4]
Archibugi et al. (1991) [1]
Cesaratto and Mangano (1993) [6]
De Marchi et al. (1996) [8]
Arvanitis and Hollenstein (2001) [9]

Services

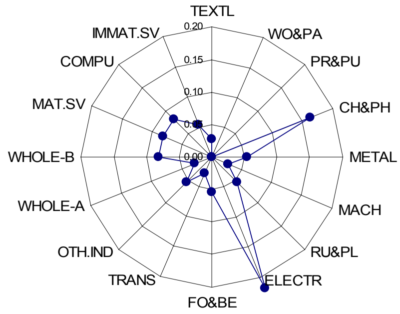
Evangelista (2000) [16]
Hollenstein (2003) [10]

Figure 3 Radar charts of conditional distributions, by innovation strategy

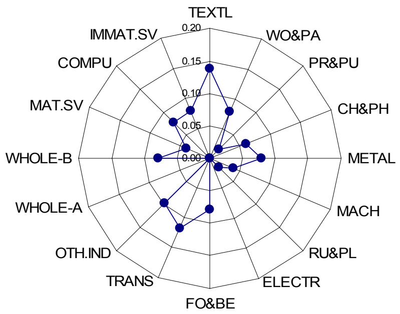
A. Science-based innovation [HI = 0.090]



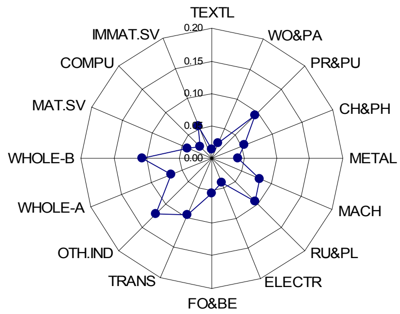
B. Development-based innovation [HI = 0.110]



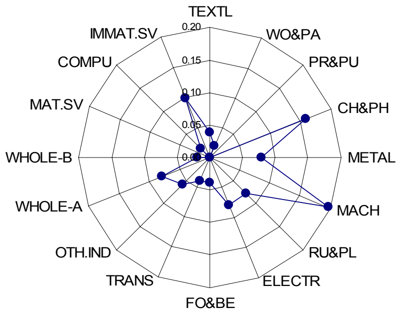
C. Resource-based innovation [HI = 0.087]



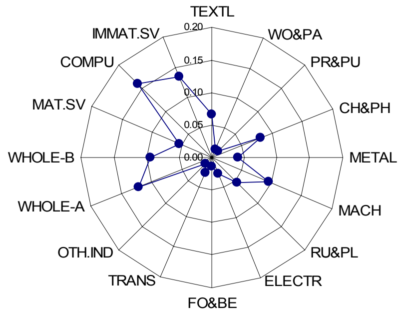
D. Market-oriented innovation [HI = 0.078]



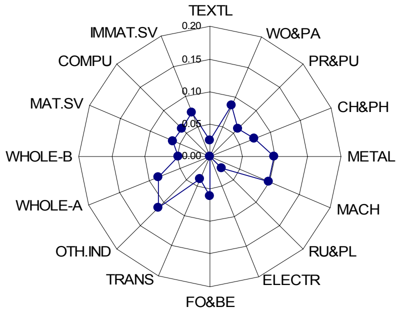
E. Research-based innovation [HI = 0.106]



F. Service-oriented innovation [HI = 0.095]



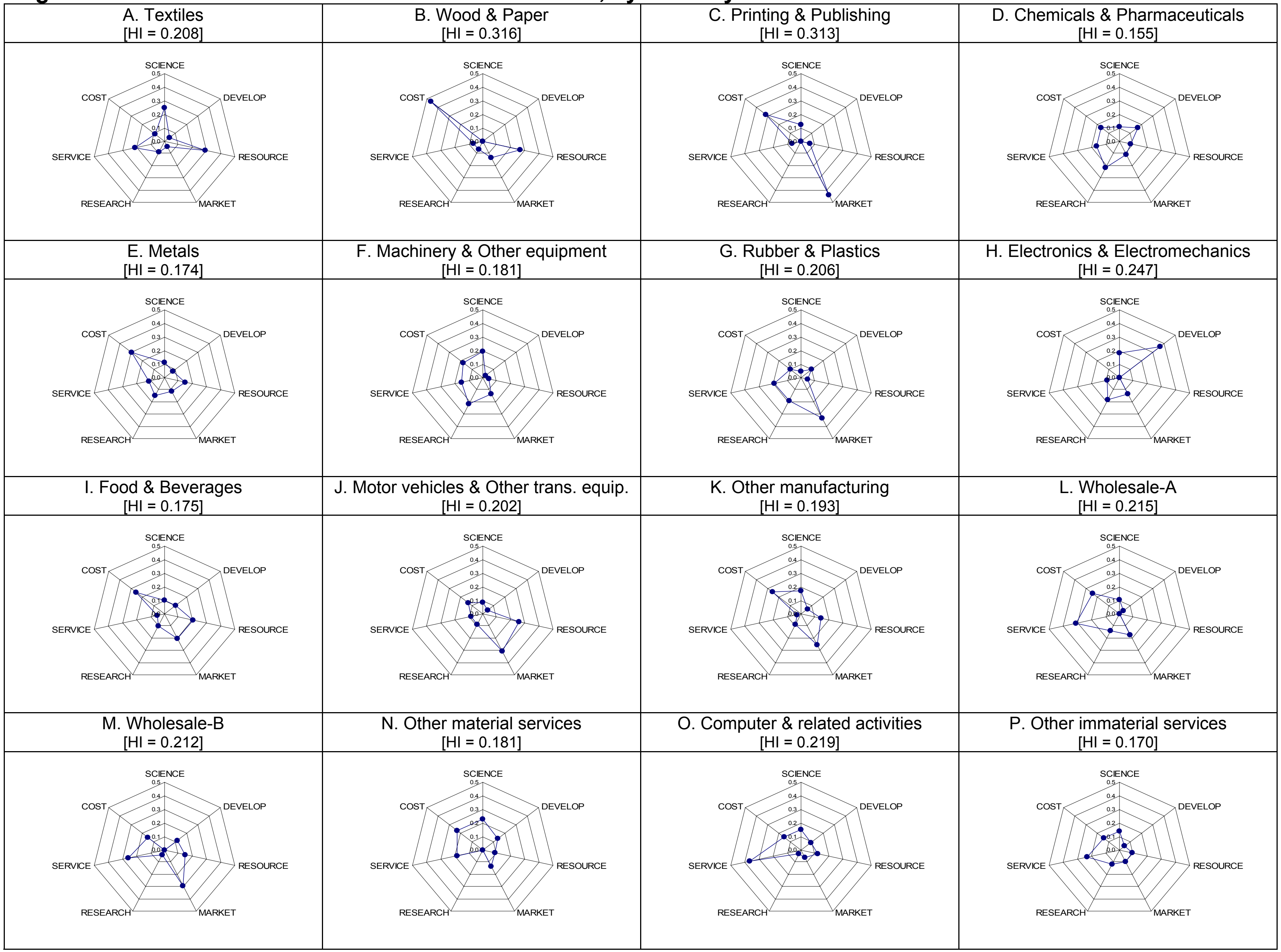
G. Cost-oriented innovation [HI = 0.076]



Definition of industries

TEXTL = Textiles
WO&PA = Wood & Paper
PR&PU = Printing & Publishing
CH&PH = Chemicals & Pharmaceuticals
METAL = Metals
MACH = Machinery & Other equipment
RU&PL = Rubber & Plastics
ELECTR = Electronics & Electro-mechanics
FO&BE = Food & Beverages
TRANS = Motor vehicles & Other transport equipment
OTH.IND = Other manufacturing
WHOLE-A/B = Wholesale-A/B
MAT.SV = Other material services
COMPU = Computer & related activities
IMMAT.SV = Other immaterial services

Figure 4 Radar charts of conditional distributions, by industry



Appendix

Table A.1 Structure of the sample and the set of 'innovative' firms

	Number of firms in the dataset	% of innovative firms
Distribution of firms by industry		
Manufacturing	400	72.7
Textiles	31	77.4
Wood/Paper	22	68.2
Publishing/Printing	19	84.2
Chemicals/Pharmaceuticals	51	80.4
Metals	42	66.7
Machinery/Equipment	60	76.7
Rubber/Plastics	28	75.0
Electronics/Electro-mechanics	33	66.7
Food/Beverages	29	69.0
Motor vehicles/Other transport equipment	31	74.2
Other Manufacturing	54	64.8
Services	273	56.4
Wholesale A	58	50.0
Wholesale B	41	65.9
Other material (transport) services	65	33.8
Computer and related activities	38	86.8
Other immaterial services	71	60.6
Distribution of firms by size class		
Small firms (10-49 employees)	419	56.8
Medium-sized firms (50-249 employees)	146	79.5
Large firms (≥250 employees)	108	84.3
Total	673	66.1

Biography

Marc Tiri

After graduating in Commercial Engineering, in 1997, Marc Tiri received his PhD degree in Applied Economics at the Limburgs Universitair Centrum (currently Hasselt University) in 2004 ('Essays on Innovation'). At present he is a post-doc researcher at the KIZOK Research Centre for Entrepreneurship and Innovation (Hasselt University). His research interests are mainly in the fields of applied econometrics (entropy econometrics, micro-econometrics), industrial organization and empirical economics of innovation.

Ludo Peeters

After graduating in Business Administration,Economics, and Social and Cultural Anthropology, Ludo Peeters received his PhD degree in Applied Economics at the Catholic University of Leuven, in 1989. In 1989-90, he worked as a post-doctoral research associate at the Department of Economics of Iowa State University (1989-90). At present, he is full professor of Econometrics at the Faculty of Applied Economics of the Hasselt University (UHasselt). His research interests are mainly in the fields of applied econometrics (Bayesian and entropy econometrics, spatial econometrics, micro-econometrics), industrial organization, regional economics (including input-output analysis), and regional innovation systems.

Gilbert Swinnen

After graduating in Applied Economics and in Commercial Engineering at the University of Antwerp (UFSIA), Gilbert Swinnen was a visiting researcher at Stanford University in 1981 (working with Prof. David Montgomery). In 1983, he received his PhD degree in Applied Economics at the University of Antwerp. At present, he is full professor of Marketing and Marketing Research at the Hasselt University (UHasselt). His research interests are mainly in the fields of marketing research (multivariate data analysis, data mining applications, choice models, customer satisfaction measurement) and distribution (strategy and retail marketing issues).