Sectoral Innovation Patterns of Small and Medium-Sized Manufacturing Firms: a Brazilian Firm-Level Analysis

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Abstract

Taxonomies of patterns of innovation that consider the small and medium enterprises (SMEs) are scarce in literature, and especially for developing countries. This paper presents a taxonomy that utilizes PINTEC-2008's microdata, a sample of innovative Brazilian manufacturing firms. The goal, through the use of a non-parametric methodology applied to this database, was to distinguish sectoral patterns for SMEs by identifying whether they influence the innovative behavior of small- and medium-sized firms. Moreover, another objective involves identifying if these influences differ from those affecting large firms. The results obtained reveal that sectoral dynamics are relevant to SMEs' innovative behavior, similar to what occurs with large companies.

Keywords: Innovation; Sectoral Patterns; Small and Medium Enterprises; ~~Pavitt´s Taxonomy;~~ Brazil.

1. Introduction

Firm heterogeneity at the sectoral level is the focus of neo-Schumpeterian and evolutionary studies, as observed in analyses of technological regimes, sectoral patterns of technical change, and sectoral systems of innovation.

Pavitt's taxonomy (1984) is commonly utilized to identify factors that affect innovation when the level of analysis is the sector. This author found similarities among firms in the same sector, and other researchers, inspired by his work but using different methodologies, could confirm the existence of significant differences between sectors regarding innovative activities.

The expressive innovative activity among small and medium-sized enterprises (SMEs) and across industries, as detailed by Pavitt (1984) and Pavit et al. (1987), have motivated studies focused on specific segments. These are expected to identify if sectoral differences are also significant to small enterprises.

The main objective of the paper was to distinguish sectoral patterns for SMEs by identifying whether they influence the innovative behavior of small- and medium-sized firms. Another objective involves identifying if these influences differ from those affecting large firms.

The study reported in this paper is part of the effort to pioneer research regarding the innovative behavior of Brazilian SMEs[1] in an attempt to identify sectoral patterns. This is a

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[1] The methodology used for grouping firms is based on workforce quantity. This methodology is adopted by the Brazilian Institute of Statistics and Geography (IBGE, in the Portuguese acronym) and by the Support Service System to Micro and Small Enterprises (Sebrae, in the Portuguese acronym), which divides companies into "micro" (up to 19 employees), "small" (from 20 to 99 employees), "medium" (from 100 to 499 employees) and "large" firms (over 499 employees), according to the number of people employed and the sector of activity. In addition, there is a statistic reasoning to cluster the SMEs versus "large" firms, as the Industrial Technological Innovation Research (PINTEC, in the Portuguese acronym) micro data database utilized is composed of sample data for SME firms, whereas it uses population data for "large" firms.

firm-level analysis, following Archibugi's (2001) research and other studies, which consider that sectoral clustering should be done in the firm's level. This procedure would minimize the variety problems within each category.

A non-parametric analysis is applied to the PINTEC-2008's microdata to fulfill the objective. In order to identify the existence of sectoral patterns of innovation for SMEs, the study applied the same methodology to SMEs and to large firms to more adequately analyze the data. Furthermore, the patterns found contrasted with Pavitt's (1984) taxonomies, and identified its applicability to SMEs.

The paper is organized in four sections other than this brief Introduction and the Conclusion. Section 1 presents relevant literature, which revolves around Pavitt's (1984) work and its application. A brief review of empirical evidence found in Brazilian studies is introduced in Section 2. The dataset and empirical method are presented in Section 3. The empirical results of sectoral influences on the innovative behavior of SMEs are analyzed in Section 4, based on innovation sources, innovation results, and innovation effort data. The Conclusion summarizes empirical implications.

2. Review of Relevant Literature

Sectoral differences, and especially in terms of innovative activity, were identified in numerous studies that preceded Pavitt's seminal work, according to Dosi et al. (1988). These analyses form the existing empirical basis for Pavitt's (1984) presentation of his taxonomy from a firm-level perspective, organizing innovative enterprises according to their structural characteristics. Pavitt (1984) intended, in presenting this taxonomy, to classify firms based on their technological competencies.

Pavitt classified firms into four industrial sector categories: (1) science-based; (2) supplier-dominated; (3) scale-intensive; and (4) specialized suppliers. This classification was revised by Tidd et al. (2001), introducing a fifth category: information intensive.

Pavitt's taxonomy intends to compare and contrast the similarities and differences across sectors in relation to innovation's sources, nature, and output, as defined by sources of knowledge and the size and primary activity of innovative firms, due to innovative sectors and their primary consumers (Pavitt, 1984).

The first taxonomic category consists of the supplier-dominated pattern, which comprises traditional industries, such as lumber, textile, wood and paper, and printing and publishing, among others. Firms are predominantly small in terms of size, and innovation activity occurs through the incorporation of technology developed across other sectors. Process innovation predominates, and cost-reduction technological trajectory dominates.

The second category involves predominantly large, scale-intensive firms, characterized by high process and product innovative efforts. However, technological trajectories are more strongly oriented to performance-increasing product innovation than to cost-reducing process innovation.

Scale-intensive firms have the protection of innovation appropriability, guaranteed by trade secrecy and patent protection, leading to technological trajectories oriented to increasing production scale and production assembly lines when opportunities for cost-reducing technical change present themselves. These firms present complementary relationships with specialized suppliers, building advanced technical trade with them. Scale-intensive firms most likely constitute a testing ground for new processes developed by specialized supplier firms, which provide designs and resources for scale-intensive enterprises.

The third category, specialized suppliers, congregates machinery, equipment, and instrumentation to focus on a technological complementary relationship. One would observe that this is due to the users' sensitivity, making the clients the source of the technological process. This explains the relatively small size of the specialized firms that supply equipment and instrumentation to the other categories, and especially presenting a complementary relationship with scale-intensive firms. Therefore, the predominant trajectories are oriented to performance-increasing product innovation, and innovation based on tacit knowledge and the accumulated experience.

Finally, the fourth category comprises science-based firms that face advanced technological opportunities, and are very sensitive to scientific knowledge development. The foremost form of learning in this pattern originated through research and development (R&D), involving high interaction with basic science research institutes. Firms' average size is relatively large, with as much product as process innovation. However, in later work Pavitt et al. (1987) stated that in these patterns, large firms coexist with smaller enterprises.

This led Pavitt (1989) in a later study to classify firms intensely linked to information and typical of service sectors, introducing "information intensive" as a fifth major pattern of innovation (Archibugi 2001). The introduction of this new category eventually caused the disappearance of the supplier-dominated pattern, which was forced to become either scale-intensive or information-intensive, or risk becoming non-innovative.

However, the withdrawal of the supplier-dominated technological trajectory could be considered a mistake, as this comprises a distinct and significant pattern of innovative firms that acquire machinery and equipment (Archibugi 2001). Therefore, the various original technological trajectories represent reality as demonstrated in Italy (Archibugi et al. 1991; Evangelista et al. 1997), Spain (Molero 1994; Urraca 1997), and Brazil (Campos and Ruiz 2009; Silva and Suzigan 2014).

Tidd et al. (2001) later revised the taxonomy and its alterations, defining a model with five categories: the original four, plus the introduction of the information-intensive category. Pavitt's ample use and extensive empirical exploration of taxonomy notwithstanding, to the present it has not been immune to varied criticism.

This criticism consists of the taxonomy's applicability, which is fitting to classify innovative firms, but unfit for non-innovativeness (Archibugi 2001). A number of non-negligible firms do not innovate, a percentage that varies across countries, but that remains even despite the methodology adopted, as those methods consider innovation beyond formal R&D.

A second criticism points out that the Pavittian taxonomy classifies firms and not industries, which in Pavitt's (1984) study were grouped at the industry level (Archibugi 2001). This represents the allocation of firms of different technological basis to the same sector. This issue reports as to intra-sector differences, as treated by Leiponen and Drejer (2007). A solution for this problem is to develop studies with firm-level data, an option adopted by this study.

The different national trajectories support a third criticism to Pavitt's taxonomy, focused on the country sectoral specificities. However, an analysis of several Brazilian studies notes that the taxonomy allows for the determination of each country's peculiarities instead of purging them, therefore providing an excellent tool for cross-country analysis (Campos and Ruiz 2009; Silva and Suzigan 2014).

Finally, there is criticism that the taxonomy is a static analysis in the face of the dynamism of capitalism (Archibugi 2001). One can argue that it is possible to understand the same taxonomy in a dynamic way if the following is considered:

> "The rise of a new category of firms has not led to the destruction of pre-existing firms. Capitalism has not destroyed pre-existing organizational forms, but it has added new ones. Schumpeterian gales of creative destruction have forced traditional firms to introduce many changes, but they have continued to follow the principal technological trajectory that they were already accustomed to. This has allowed them to continue to co-exist with new firms characterized by a different trajectory. (...) This suggests that the same taxonomy may be used to explore the parallel long-term evolution of corporations and of economic activity (…)" (Archibugi 2001, 423).

Despite the criticism, Pavitt's (1984) taxonomy, used as the main thread throughout this paper, has its theoretical value and empirical applicability recognized in the ongoing debate.

3. Brazilian Empirical Evidence

Brazilian theoretical and empirical literature regarding innovative activity determines that some studies attempted to understand the sectoral differences of industrial innovation determinants. While the majority of these studies' datasets involve PINTEC's microdata held by IBGE from 2000, 2003, 2005, 2008, and 2011), few studies use taxonomies, as it is more common to use technology intensity indicators.

The point of departure for such studies is the PINTEC-2000 microdata. Relevant research found in the work of Kannebley et al. (2004) demonstrates the efforts to characterize the Brazilian innovative firm. It aims to identify innovative firms' characteristics using a non-parametric analysis. This study elicited that the sectoral analysis, isolated, is incapable of identifying innovation parameters.

De Negri and Salerno (2005) report a detailed analysis of Brazilian innovative firms. This research made clear that Brazilian enterprises that innovate and differentiate products can improve their share in foreign markets, therefore capable of greater growth.

Brazilian innovative companies in the study correspond to only 1.7% of the Brazilian industry, according to PINTEC-2000's data, but represent 25.9% of the industrial revenues and generate 13.2% of the industry's employment. This also highlights that Brazilian firms' technological behavior is impacted by the sector in which the company operates.

Kupfer and Rocha (2005) analyze the Brazilian competitive sectoral strategies in this same context, concluding that firms with innovative performance are concentrated, for the period of analysis, in the mechanical, chemical, and electronics industries, corresponding to 61.6% of all firms that innovate and differentiate products. However, beyond those findings, the research notes that firms innovate and differentiate products in all sectors of the industry, thus making innovation a horizontal phenomenon, a competitive strategy used by Brazilian firms across all industries.

Other studies used non-parametric analysis, such as multivariate techniques, to identify Brazilian firms' sectoral patterns and characteristics. The work of Gonçalves and Simões

(2005) is a study among these that deserves mention, as it analyzes the different types of innovation process expenses.

Another relevant study is that of Campos and Ruiz (2009), which uses hierarchical and non-hierarchical cluster analyses. Based on PINTEC-2000's dataset, this study recognized sectoral patterns of innovation in the Brazilian industry, based upon five innovation traces (innovation sources, knowledge and learning processes, technological trajectories, innovation processes' output, and performance and structural characteristics). This study concluded that Brazilian industry's sectoral diversity is significant and cannot be neglected by industrial policies.

The work of Maia (2012) and Maia and Botelho (2014) evaluated the sectoral differences of small firms' innovative activity, concluding that the innovative efforts of small companies stands out relative to larger firms for the PINTEC-2008 dataset. These results indicate the relevance of SMEs in Brazilian innovative activity, eliciting the expressive sectoral diversity, in terms of efforts, of SMEs' innovative activity.

Nogueira and Oliveira (2013) explore micro- and small-sized firms' diversity, noting that this group cannot be characterized by one dimension, as it is necessary to develop typologies capable of expressing different-sized companies' heterogeneity. The authors propose the development of taxonomies that express the maturity of firms that composes them and the building blocks of government policies to comply with groups' specificities. Thus, Nogueira and Oliveira's (2013) main proposal corroborates the aim of this paper.

Finally, Zucoloto and Nogueira (2013) emphasized the importance of resource supply to small companies in a way that, despite having a smaller innovation rate than larger companies, they represent the bigger innovative firms' group, defining what makes them relevant to national technological development. Concluding remarks corroborate the results found by Botelho et al. (2012), which determine a negative relationship between innovative efforts and firm size.

Despite identifying important aspects of the innovative activities of Brazilian companies, these studies did not advance the discussion of the sectoral component of the innovative activities of SMEs. This paper intend to cover the literature gap.

4. Database and Methodology

This study primarily uses the Industrial Technological Innovation Research (PINTEC) database for the year 2008. This database consists of a broader official survey regarding Brazilian technological innovation information in industry. The PINTEC survey, conducted by IBGE, respects the international methodology for innovation research in conformity with the Oslo and Bogota Manual, specific for developing countries.

Research quality in this area has evolved, as in the case of the CIS 2008 (Science Technology and Innovation Europe, 2008) and the Technological Innovation Research (PINTEC) from 2008 and 2011, which allows for a set of information regarding the technological change process, such as informal R&D activities. The new data form allows for a superior analysis of small firms that repeatedly use configurations of innovation other than formal R&D.

The majority of sectoral analyses are based on sectoral-level and industry data at an intermediate classification level from the National Classification of Economic Activities (CNAE), or between two and three digits (IBGE, 2008). However, this paper explores a firm-level analysis, and reports the results at the industry level at two digits, or the level allowed by

IBGE due to confidentiality issues. The adopted breakdown[2] ensures the statistical representation of each sectors' information for each group size without compromising the data's secrecy. This also allows for a test to determine if the firms in the same industry present similar innovation patterns (Archibugi 2001; De Jong and Marsili 2006).

The firm-level analysis was embedded in PINTEC-2008's survey, which represents a sample of 96,792 small- and medium-sized companies, in which 36,746 are innovative firms; and 1,628 are large firms with 1,176 that are innovative, totaling 98,420 manufacturing firms. The present analysis uses manufacturing product and process data regarding innovative firms that contrasts SMEs' innovative behavior (with less than 499 employees) and that of large firms (with more than 499 employees).

A cluster analysis was applied to key variables to study the innovative activity used, or permitted building sectoral patterns. This cluster analysis, also known as a conglomerate or grouping analysis, "(...) has the aim to (classify) divide the sample or population elements into groups, in a way that the elements that belong to a same group are similar among themselves regarding the variables (characteristics) that measured them, and the elements in different groups are heterogeneous in relation to those same characteristics" (Mingoti 2005, 155).

Among the specific uses of conglomerate analysis is "data mining," related to the use of computational tools in the search for patterns in the data analysis, or in the pursuit to determine typologies. The present study uses the conglomerate analysis as a tool to verify if Pavitt's taxonomy can be used for PINTEC-2008's SME firms.

The special statistics produced, through the use of PINTEC's microdata (IBGE 2008), uses chosen variables aimed to define an innovative pattern that respects the one developed by Pavitt (1984), the limitations of the accessibility of PINTEC's data (IBGE's openness and allowed breakdown), as well as the cluster analysis' methodology.

Therefore, classifying variables widely used in empirical studies into three groups provided the cluster analysis a basis to identify sectoral technological efforts, such as: (1) firm innovation sources, both internal and external, according to De Jong and Marsili (2006); (2) innovation output, product, and process innovation (Campos and Ruiz 2009); (3) innovative efforts (Leiponen and Drejer 2007).

As illustrated in Table 1, the first block of grouped variables relates to "relevant innovation sources," regarding the relevance of innovation activity input.

The set of variables that conform to the first group consists of the relevance of R&D, design, training, marketing, machinery and Equipment (M&E), and external knowledge, embedded in the works of Acs and Audretsch (1988, 1990), De Marchi et al. (1996), Evangelista (2000), Freel (2003), and Bhattacharya and Bloch (2004). The second block consists of innovation output subsets. This study relied upon these variables to generate the clusters for SMEs' and large firms' outputs, for comparative procedures according to the studies of Pavitt (1984), Archibugi et al. (1991), De Marchi et al. (1996) and Tid et al. (2001). The third grouping addresses innovative efforts (Leiponen and Drejer 2007).

It is expected that the use of cluster analysis allows for the classification of data into four groups that respect Pavitt's taxonomy, which have been tested by De Jong and Marsili (2006) for SMEs: (1) science-based sectors; (2) specialized-supplier sectors; (3) scale-intensive

[2] New Brazilian regulation no longer allows the breakdown sectoral data by size, therefore the research developed is singular.

sectors; and (4) supply-dominated sectors. This stage of the study aims to confirm if it is possible to apply this classification to Brazilian SMEs.

The technological trajectories defined in the original taxonomy were sustained, meaning that the "scale-intensive" grouping was not substituted by the insertion of the "information-intensive" pattern, as suggested by De Jong and Marsili (2006), as the analysis dealt exclusively with manufacturing firms, and the new information-intensive category relates to service sectors. Furthermore, as suggested by Archibugi (2001), the decision to exclude trajectories from the original taxonomy is not recommended, as studies such as those conducted in Italy (Archibugi et al. 1991; Evangelista et al. 1997) confirm the importance of original trajectories.

The cluster analysis, using hierarchical and non-hierarchical methods adopting similarity and dissimilarity measures, is the subset of tools selected for the research's empirical stage. The classification, as suggested by Everitt et al. (2011), can provide a concise description of similar and dissimilar patterns.

This technique is sometimes denoted as taxonomy, pattern recognition, and even segmentation, but cluster analysis is currently the preferred term to determine the procedure that observes data grouping. The data partition, or a search in such a way that each object or objects belong to a sole cluster, and the complete group of clusters contains all objects, is the most usual application of this methodology.

The hierarchical cluster analysis consists of successive data fusions and divisions, and once the algorithm allocates an object, it is irrevocable. The hierarchical method can be agglomerative, or perform successive divisions.

The agglomerative method carries on the fusions of *n* objects into groups; the divisive method subdivides a group of *n* objects into even more specific groups (Dillon and Goldstein, 1984). The first equation presents N forms to partition the *n* objects of *k* groups.

$$N(n,k)=\frac{1}{k!}\sum_{g=1}^{k}\binom{k}{g}(-1)^{k-g}g^{n} \tag{1}$$

Where:

N - Number of ways to partition; n - quantity of objects; and k - quantity of groups.

The non-hierarchical technique merges cases, instead of variables, into groups of clusters, in which the number of groups are specified at the beginning of the process; the same applies to the outcome of an agglomerative method. The non-hierarchical cluster monotonically increases its ranking as the clusters become a part of bigger clusters. These methods of grouping objects, agglomerative or divisive clusters, lack tree structures, and new clusters are formed successively.

The K-Means clustering (Equation 2) is one of many non-hierarchical measures. It designates each item to the cluster that has the center closest to the average.

This method attempts to minimize the sum of the variances across clusters.

$$V_k=\sum_{k=1}^{K}\sum_{i=1}^{n}\delta_{ik}m_i d^2(x_i-\bar{x}_k) \tag{2}$$

The function indicator δ_{ik} equals 1 if the observation x_i comes from cluster ***k***, or zero in the contrary. The $\bar{x}_{kj}$ element of the $\bar{x}_k$ vector is the average of the *j* variables in the ***k*** cluster.

$$x_{kj} = \frac{1}{n_k}\sum_{i=1}^{I}\delta_{ik}m_i x_{ij} \tag{3}$$

The criterion of the K-means method, one of many methodologies, can be directly determined using the maximum likelihood estimation, assuming that the population is independent and normally distributed. As a way to evaluate the partition groups, confirming the statistical significance of the resulting grouping, validation tools were used, such as pseudo F-statistics and the squared pseudo-T.

The Calinski-Harabasz pseudo-F (Equation 4) describes the ratio of the variance across clusters in relation to the variance's inter-cluster (Calinski and Harabasz 1974). The pseudo-F is a test that identifies the number of clusters using a statistic that identifies the correct number of clusters when a rupture in pattern is presented to the other pseudo-F groups; that is, a value smaller than others are.

$$Pseudo-F = \frac{(GSS)/(K-1)}{(WSS)/(N-K)} \tag{4}$$

Where:

N - number of observations; K - number of *clusters* at each phase of the hierarchical grouping; GSS - squared-sum across groups; WSS - squared-sum inter-group.

High values for the pseudo-F Calinski-Harabasz indicator identifies distinct groups.

Table 1 – Description of variables used in the cluster analysis.

Cluster	Variable Name		Variable Nº PINTEC (2008)
1. Relevant Innovation Sources	Internal	R&D	High relevance attributed to internal R&D V24
		Product Design (Design)	High relevance attributed to the development of new industrial projects and other technical preparations V30
		Training	High relevance attributed to training V28
		Marketing (Mkt)	High relevance attributed to marketing innovation V29
	External	External R&D (E-R&D)	High relevance attributed to external R&D V25
		External Knowledge (E-KNW)	High relevance attributed to other external knowledge V26
		Machinery and Equipment (M&E)	High relevance attributed to acquisition of machinery and equipment V27
2. Innovation Outputs	Product Innovation		Firms that innovate in products new to the firm and the industry V10, V11
	Process Innovation		Firms that innovate in processes new to the firm and the industry VA_16_17; VA_16_17_1; VA_16_17_2
	Radical Product Innovation (prodrad)		Firms that innovate in products new to the industry V11
	Radical Process Innovation (procrad)		Firms that innovate in processes new to the industry V17
	Incremental Product Innovation (prodincr)		Firms that innovate in products new to the firm, but not new to the industry V10
	Incremental Process Innovation (procincr)		Firms that innovate in processes new to the firm, but not new to the industry V16
	Patenting Firm (patent)		Firms with patents in Brazil or abroad V163, V164
	Marketing Innovation (Inovamkt)		Proportion of innovation in marketing. INOVMKT
3. Innovation Efforts	R&D		R&D Expenditure (R$)/Sales Revenue V31/RECLIQ
	Product Design		Product Design Expenditure (R$)/Sales Revenue V37/RECLIQ
	Training		Training Expenditure/Sales Revenue V35/RECLIQ
	Marketing		Marketing Expenditure/Sales Revenue V36/RECLIQ
	External R&D		External R&D Expenditure/Sales Revenue V32/RECLIQ
	External Knowledge		External Knowledge Expenditure/Sales Revenue V33/RECLIQ
	M&E		Machinery and Equipment Expenditure/Sales Revenue V34/RECLIQ

If it is supposed that during the hierarchical grouping stage, the K e L clusters unite to form a new cluster, the pseudo T-squared statistic (Equation 5) for the new cluster is given by:

$$Pseudo - T \ squared = \frac{B_{KL}}{((W_K + W_L)/(N_K + N_L - 2))} \tag{5}$$

Where:

N_K - number of observations on K cluster; N_L - number of observations on L cluster; W_K - internal squared sum of K cluster; W_L - internal squares sum of L cluster; e, B_{KL} - squared sum across clusters*;*

5. Results: Innovation patterns for Brazilian small- to medium-sized enterprises

This section, which contains the main body of the article, consists of three sub-sections to present the data related to relevant innovation sources, innovation process and product outputs, and innovation efforts.

5.1 Innovation Sources: the patterns for small- to medium-sized enterprises

The definition of innovation sources occurs according to the locus, in which innovative activities are conducted. The literature distinguishes between innovation sources that correspond to input in the innovation process, and those that represent knowledge sources (Mansfield and Rapoports 1975; Ruiz and Bhawan 2010).

Regarding the different loci of innovative activity development, the innovative efforts employed inside firms are enveloped by the term "internal innovation sources." Whereas the external innovation process consists of initiatives that generate technical change originated in other loci, outside the firm, the latter are incorporated with the enterprise through the market, even marginally.

There are four internal innovation sources (R&D, product design, training, and marketing) and three external innovation sources (external R&D, external knowledge, and machinery and equipment (M&E)) identified by PINTEC-2008 and presented in Table 1. These variables were generated for the group of small- to medium-sized product and process innovative firms, measured by the high importance firms attributed to the different innovation sources.

The statistical results, as indicated by the Calinski-Harabasz pseudo-F[3] legitimize the groups' partition. The pseudo-F presented the highest relative value of 66.98 for the partition of four clusters, corroborated by a Duda/Hart Je(2)/Je(1), with high results. In this manner, the Calinski-Harabasz pseudo-F indicated statistically that there were four clusters, confirmed by a pseudo-T^2 of 6.74, which is significantly low.

The R-squared (R^2) confirmed the statistical significance of the clustering configuration. Therefore, for innovation sources, the variables used in this analysis prove considerably significant, with an R-squared (R^2) of 88.87, as verified in Table 2. This table discloses the performance of the innovation sources' relevance magnitude across sectors.

[3] This test is performed using Stata (11.0) to evaluate the group partition. The test identifies the number of clusters when validating a pseudo-F for the adequate cluster that breaks with the behavior pattern of the pseudo-F for all other clustering, presenting the lowest values of all.

Table 2 – SMEs Cluster analysis: relevance of innovation sources.

Cluster	Industry	R&D	Design	Training	Marketing	External R&D	External Knowledge	M&E
		Internal Sources				External Sources		
	Brazil (Manufacturing)	*0.068*	*0.233*	*0.432*	*0.175*	*0.028*	*0.074*	*0.616*
1	Beverages	0.052	0.339	0.398	0.182	0.020	0.048	0.618
1	Motor Vehicles	0.110	0.304	0.403	0.135	0.059	0.117	0.549
1	Machinery and Equipment	0.112	0.307	0.352	0.139	0.049	0.067	0.576
1	Tobacco	-	0.285	0.266	0.192	-	-	0.362
1	Leather and Footwear	0.056	0.269	0.369	0.181	0.001	0.071	0.590
1	*Cluster Average*	*0.098*	*0.226*	*0.453*	*0.168*	*0.016*	*0.076*	*0.647*
2	Apparel and Luxury Goods	0.017	0.188	0.415	0.167	0.007	0.068	0.640
2	Metallurgy	0.041	0.228	0.401	0.062	0.005	0.026	0.646
2	Instrumentation	0.022	0.253	0.618	0.119	0.010	0.074	0.741
2	Furniture	0.005	0.218	0.469	0.120	0.063	0.068	0.594
2	Textiles	0.026	0.208	0.380	0.081	0.002	0.039	0.581
2	Lumber Products	0.006	0.227	0.449	0.063	-	0.033	0.615
2	Metal Product	0.044	0.214	0.484	0.078	0.011	0.074	0.623
2	Non-Metallic Mineral Products	0.013	0.234	0.372	0.071	0.023	0.029	0.733
2	*Cluster Average*	*0.022*	*0.219*	*0.396*	*0.130*	*0.017*	*0.065*	*0.656*
3	Paper and Forestry	0.016	0.177	0.390	0.224	0.039	0.070	0.720
3	Printing and Publishing	0.048	0.112	0.497	0.235	-	0.181	0.760
3	Transport Equipment	0.071	0.183	0.320	0.174	0.012	0.040	0.742
3	Electrical Equipment	0.167	0.217	0.517	0.211	0.010	0.112	0.574
3	Food	0.051	0.243	0.412	0.250	0.054	0.087	0.647
3	*Cluster Average*	*0.065*	*0.165*	*0.405*	*0.200*	*0.014*	*0.089*	*0.716*
4	Chemicals	0.242	0.248	0.347	0.210	0.060	0.077	0.469
4	Coal Production and Oil Refining	0.217	0.420	0.415	0.280	0.012	0.042	0.663
4	Electronic Equipment/Internet and Communications Equipment	0.312	0.362	0.545	0.386	0.069	0.134	0.392
4	Pharmaceuticals and Biotechnology	0.322	0.393	0.568	0.446	0.083	0.090	0.485
4	*Cluster Average*	*0.317*	*0.377*	*0.556*	*0.416*	*0.076*	*0.112*	*0.438*

$R^2 = 0.8887$

Source: PINTEC 2008.

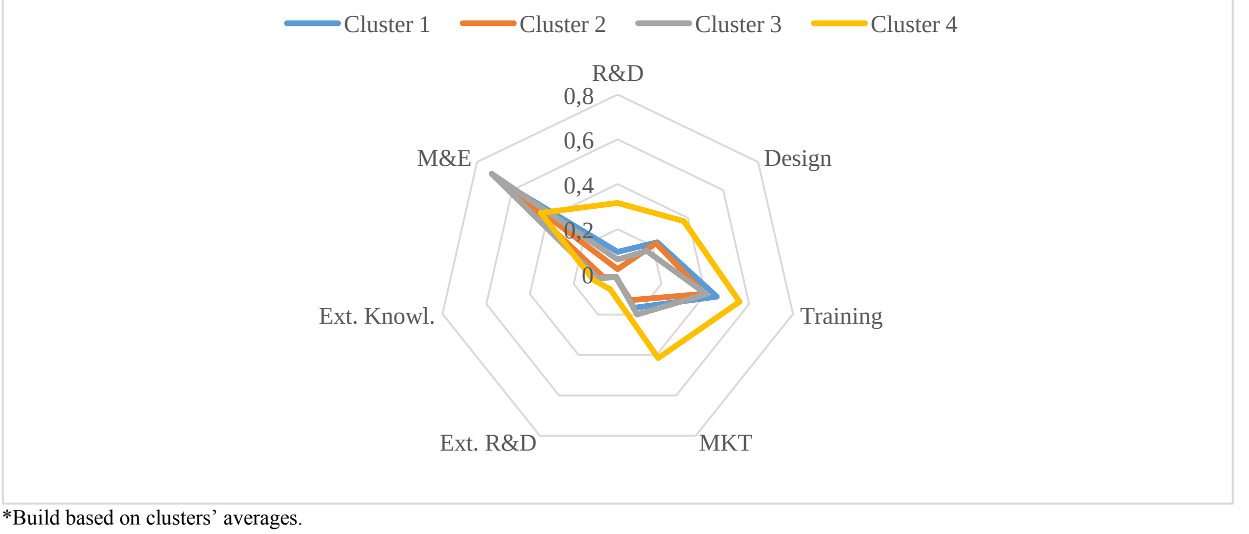
The first cluster's highlight is the importance of external sources, characterizing sectors as technology receivers. The second cluster discloses low technological dynamism, attributing high importance to marketing. The third cluster is highly associated with the acquisition of machinery and equipment, while the fourth cluster demonstrates the relevance of research and development. Finally, other conclusions are summarized in Table 3.

Table 3 – Clusters' characteristics summary according to the relevance of innovation sources for SMEs – PINTEC 2008

	Cluster 1	*Cluster* 2	*Cluster* 3	*Cluster* 4
Higher relevance	Relevance of external innovation sources (no External R&D)	Mkt e Product Design	M&E Relevance (above national average and others)	High importance of all innovation sources, Internal R&D 5 times national average.
Lower relevance	-	Relevance of External sources.	Internal Innovation (not very relevant)	Lower Relevance of M&E for all groups
Highlight Sectors	Assembly and traditional lines	Textiles, Furniture and Apparel and Luxury Goods	Electrical Equipment suggests variability	Pharmaceuticals and chemicals, Electronic Equipment/Internet and Communication Equipment
Sectors Profile	Technology receivers	Low technological dynamics	Higher incorporation of M&E	High technological opportunities

The performance of each cluster is shown graphically in Figure 1, which exposes the patterns of the average intensity of the relevance attributed to internal or external innovation sources by the different clustering. The graph confirms that the higher magnitude of relevance is validated for all innovative sources in cluster 4, whether internal or external. While clusters 1 and 3 are low, highlighting internal technological dynamism, they face higher concern with "learning by using," through the acquisition of machinery. Meanwhile, cluster 2 discloses a group with less support for innovation, and little relevance for internal or external innovation sources.

Figure 1 – Pattern dimensions according to relevance of innovation sources for SMEs.



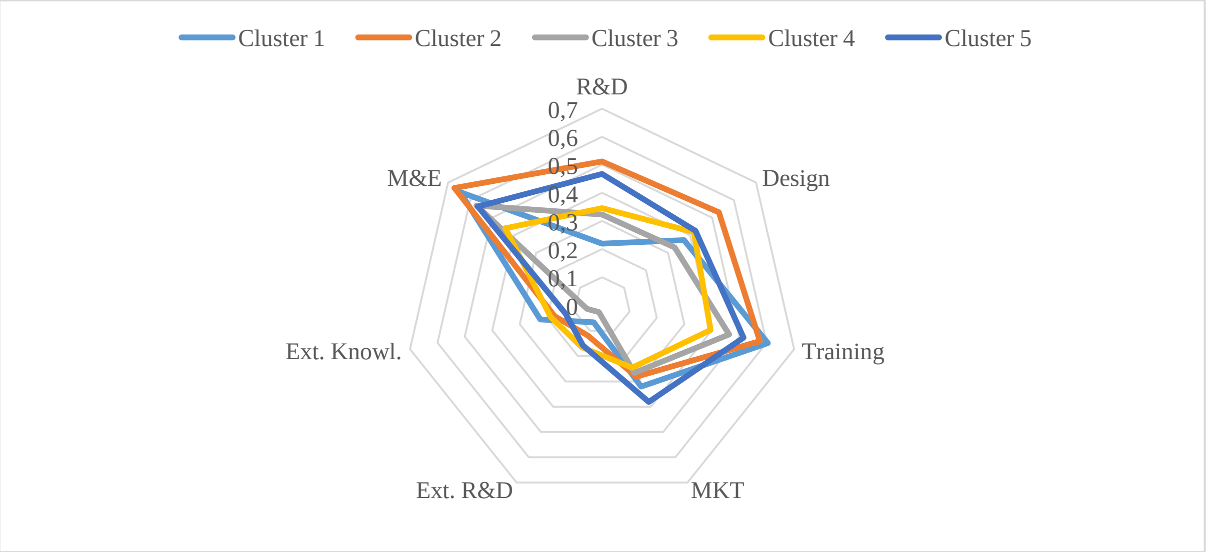
*Build based on clusters' averages.

The cluster analysis is applied likewise to large firms, contrasting the results to those of small- and medium-sized enterprises.[4]

[4] The research that generated this article performed all tests separately for small- and medium-sized enterprises, as well as for large firms. For reasons of space availability, not all results are presented here in detail. Additionally, given the article's primary objective to present sectoral patterns for small- and medium-sized enterprises, the option was not to present the results for large firms in detail, but rather, to use them for comparison purposes.

The five dimensions illustrated in Figure 2 indicate each cluster's highlighted elements. Five different clusters were also identified for the innovation sources' variables in large firms, which demonstrates a greater variability in the combination of external and internal knowledge sources. Additionally, as expected, large firms were characterized by a higher-level relevance for R&D expenditures.

Figure 2 - Pattern dimensions by relevance of innovation sources for Large Firms.



* Build based on clusters' averages

The first cluster highlights the importance of external sources, indicating technology-receiving sectors. Certain technological dynamics in the second cluster indicates the relevance of all innovation sources, attributing special relevance to the internal innovation source of R&D. The third cluster, as observed, is associated with the acquisition of machinery and equipment, while the fourth cluster presents a high association with internal and external research and development, as well as external knowledge. Finally, the fifth cluster demonstrates the high relevance of research and development facing high technological opportunities.

A comparison of information is displayed in Figures 1 and 2, identifying strong similarities among clusters 2 and 4 for SMEs, and clusters 3 and 5 for large firms. Cluster 2 (SMEs) and cluster 4 (large firms) associate closely with the supplier-dominated pattern of Pavitt's taxonomy, as characterized by such sectors as textiles and furniture. Clusters 4 (SMEs) and 5 (large firms) also disclosed similarity and support resembling the science-based sectors from Pavitt's taxonomy. The industries are the same in both groupings, such as: pharmaceuticals-chemicals, and electronics equipment-Internet and communications equipment.

5.2 Innovative Output: SMEs' patterns

According to Archibugi et al. (199l; Archibugi 2001), a diversity of empirical studies uses industry's innovative outputs to validate the results of technological change, as well as different ways of interpreting it. The sole apparent consensus is that industries demonstrate different methods of applying technological change; this would make an analysis of the entire scenario imprudent and practically impossible, based only upon one or a small group of variables, ratifying the need for specific, detailed measuring tools, as proposed by De Marchi et al. (1996).

The characterization used presents a variety of output results, avoiding an understanding of innovation output only through traditional patent measures, and especially when analyzing different firm sizes. The paper conducted a qualitative innovation characterization, classifying product and process innovation as radical or incremental to allow for the rigor of scientific validation necessary to understand the inter-sectors' output (Pavitt 1984, 1988).

The Calinski-Harabasz pseudo-F test statistically identified the number of clusters, which corresponded to four groupings: pseudo-F of 72.56, with Duda/Hart Je(2)/Je(1) of 0.678, and a pseudo-T^2 of 7.12. The groupings illustrated in Table 4 classify clusters by sectors, already partitioned into four clusters resulting from the statistic simulation, in relation to the innovation output.

As noted in Table 4, it is possible to verify that the diverse innovative sectoral performance can be explained by the chosen variables, as confirmed by the R-squared of 82.94%.

Table 4 – Cluster analysis for SMEs innovative output.

Cluster	Sectors	Product Innovation Output			Process Innovation Output				
		Product Innovation	Incremental Product Innovation	Radical Prod. Innov.	Process Innov.	Incremental Process Innovation	Radical Process Innov.	Patents	Inovamkt
	Brazil (Manufacturing Ind.)	22.6%	19.8%	3.8%	31.8%	30.6%	2.0%	6.7%	17.5%
1	Beverages	19.2%	16.8%	2.5%	25.3%	25.2%	0.3%	29.5%	6.0%
	Transport Equipment	12.7%	8.0%	5.5%	31.1%	30.1%	1.6%	12.3%	7.1%
	Rubber and Plastic Products	25.4%	21.8%	4.8%	28.7%	27.7%	2.9%	15.2%	14.0%
	Coke Production and Oil Refining	24.5%	23.5%	2.0%	42.7%	36.9%	7.8%	15.9%	11.9%
	Other Industries	23.8%	18.9%	6.4%	30.3%	26.4%	7.2%	12.9%	13.8%
	Food	24.5%	22.2%	3.8%	30.6%	28.3%	2.6%	29.5%	9.4%
	Printing and Publishing	19.7%	17.9%	1.9%	45.3%	44.4%	1.3%	1.8%	11.3%
	Cluster Average	*22.7%*	*19.8%*	*3.8%*	*31.6%*	*30.3%*	*2.8%*	*17.2%*	*9.2%*
2	Leather and Footwear	24.2%	23.8%	0.6%	32.3%	32.0%	0.4%	1.7%	7.1%
	Paper and Forestry	24.8%	23.8%	2.0%	33.4%	32.9%	1.5%	4.4%	4.7%
	Apparel and Luxury Goods	19.4%	17.8%	1.6%	33.3%	32.8%	1.7%	0.3%	5.8%
	Metallurgy	18.9%	16.1%	2.8%	30.6%	29.1%	1.6%	3.8%	4.4%
	Furniture	21.9%	19.6%	2.7%	28.3%	27.9%	0.4%	4.7%	7.0%
	Textiles	21.4%	17.3%	4.4%	29.1%	27.5%	1.9%	0.7%	7.6%
	Metal Products	19.2%	17.2%	2.9%	34.6%	33.1%	3.4%	7.5%	8.1%
	Motor Vehicles	28.1%	22.1%	10.0%	35.4%	34.2%	1.5%	6.2%	10.4%
	Cluster Average	*22.9%*	*21.0%*	*3.4%*	*35.5%*	*30.3%*	*1.5%*	*3.5%*	*6.9%*
3	Instrumentation	15.4%	12.6%	3.2%	21.9%	20.7%	1.6%	15.1%	6.8%
	Tobacco	13.3%	10.4%	2.9%	13.0%	13.0%	-	9.6%	5.9%
	Lumber Products	12.9%	12.8%	0.6%	19.5%	18.0%	2.9%	0.2%	2.4%
	Non-Metallic Minerals Products	13.9%	13.5%	1.1%	28.3%	28.0%	0.4%	3.5%	6.3%
	Cluster Average	*14.5%*	*12.3%*	*2.6%*	*23.1%*	*22.4%*	*1.1%*	*11.7%*	*5.7%*
4	Electrical Equipment	33.7%	25.1%	10.2%	34.6%	33.4%	1.5%	19.5%	21.8%
	Electronics Equipment & Internet and Communications Equip.	42.3%	31.9%	13.7%	36.1%	34.1%	2.7%	8.1%	23.9%
	Chemicals	44.5%	40.1%	10.1%	41.9%	40.4%	2.8%	9.4%	19.0%
	Pharmaceuticals and Biotechnology	44.1%	32.6%	13.9%	40.3%	39.4%	3.3%	10.9%	36.0%
	Machinery and Equipment	31.6%	24.1%	9.6%	37.8%	36.7%	1.3%	20.7%	13.5%
	Cluster Average	*38.3%*	*29.8%*	*11.3%*	*37.5%*	*36.2%*	*2.3%*	*14.6%*	*22.6%*

$R^2 = 0.8294$

Source: PINTEC 2008.

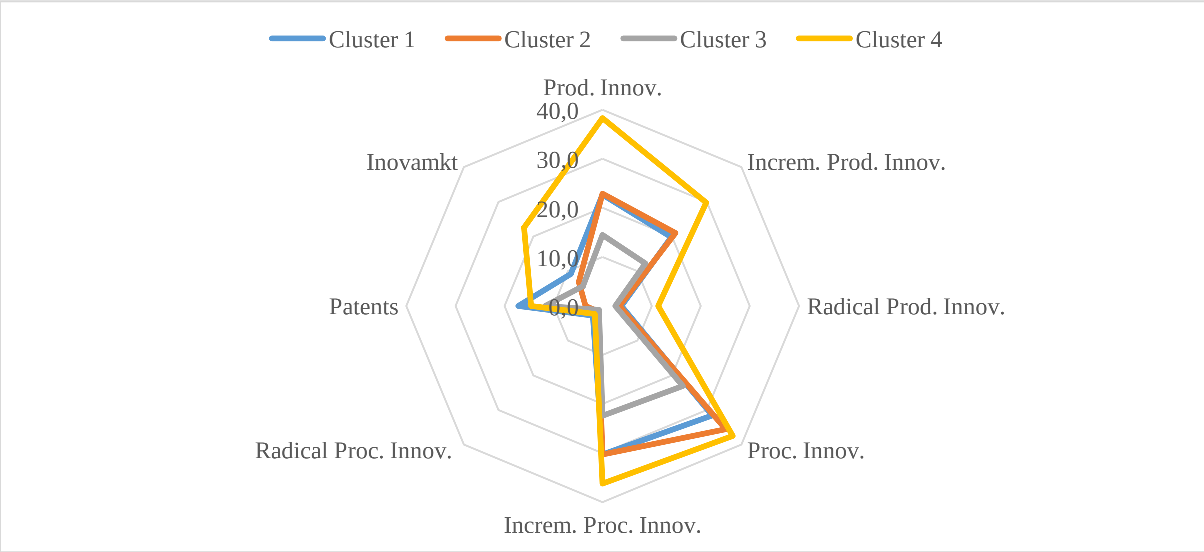
A summary of characteristics is presented in Table 5, in terms of the SMEs' innovative outputs. The first cluster displays an average degree of innovation, with more process than product innovation, revolving around radical process innovation and formal protection in the forms of patents expressly noted above the national average. The second cluster presents average innovation, with predominantly incremental innovation and low formal protection. The third cluster discloses low innovative activity, but adoption of formal protection is observed. Finally, the fourth cluster demonstrates high technological opportunities, with expressive innovative product and process output significantly and formally protected.

Table 5 – SMEs´ clusters characteristics summary according to innovative outputs – PINTEC 2008.

	Cluster 1	*Cluster* 2	*Cluster* 3	*Cluster* 4
Degree of Innovativeness/ Highlights	Average – radical process	Average –process innovation	Low	High Technological Opportunities
Product/Process	Process – significant. Product – less.	Process – significant; above Nat. average	Low innovativeness – process trajectory	Product and Process significant
Mkt	Below national average.	Low	Low	Highly significant
Radical	Radical process – above Natl average	Low	Low	Radical Innov. 3x times National Average.
Incremental	Product/process at national average	Process Trajectory	Low	Expressive
Sectors	Food; Beverage.	Furniture; Apparel; Textiles.	Tobacco; Lumber, Non-Metallic Minerals.	Chemical; Pharmaceuticals; Electrical/Electronics
Patents	Expressive 2,6x times Nat. average.	Low formal protection	Protection present	Significant formal protection

The comparison of Figures 3 and 4 demonstrates the results for SMEs and large firms, respectively, revealing the main dissimilarities between the different-sized firms in relation to innovation activity. Innovation output similarities between the different-sized firms are significant, corroborating the findings regarding the relevance of innovation sources.

Figure 3 – Patterns Dimensions* by innovation output - for SMEs.

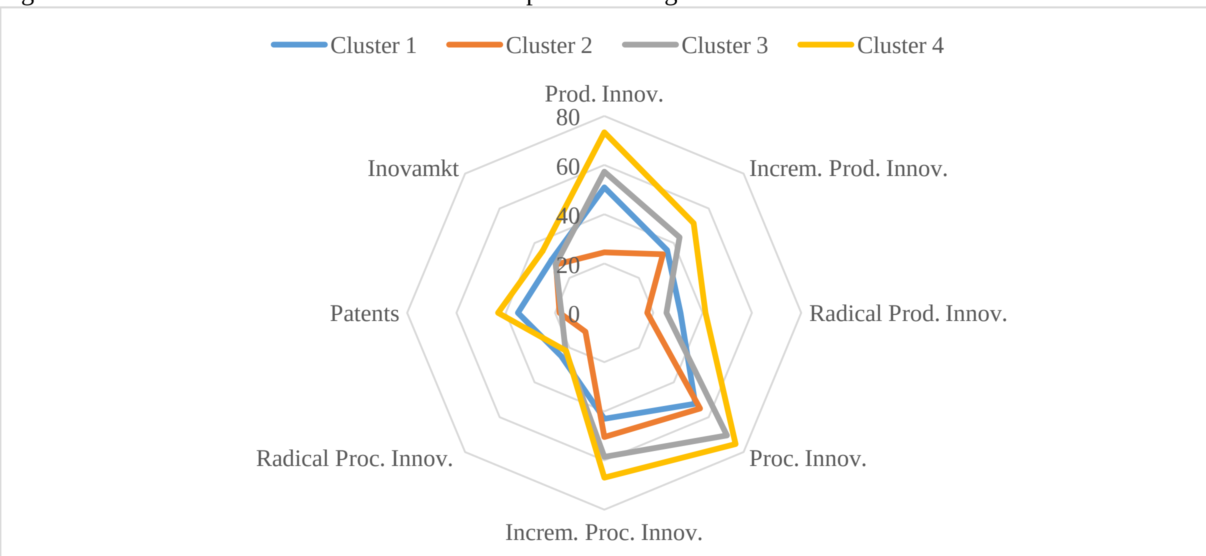


* Build based on clusters' averages.

Four clusters were confirmed for SMEs as well as large firms, with greater similarities supported in clusters 2 and 4. Incremental process innovation is observed in cluster 2 (for SMEs and large firms), with low levels of formal protection and traditional reference industries, such as furniture, apparel, and textiles. Cluster 4 (SMEs and large firms) has a greater technological dynamism, identified by the combination of radical product and process innovation that is expressly, formally protected. The pharmaceutical, chemical, and electronics industries characterize this group.

Clusters 1 and 3 disclose important dissimilarities between SMEs and large firms. The first clusters suggest that large firms' innovation is above the national average for large firms, with radical product and process innovation and greater formal market protection. All indicators analyzed in cluster 3 are lower for SMEs, relatively identifying a more dynamic grouping for large firms.

Figure 4 - Pattern dimensions* for innovation outputs – for large firms



* Build based on clusters' averages.

This characterization presents a certain degree of specialization in the innovation output, indicating more than a mere specification of variation gradient or innovation intensity. Therefore, the resulting taxonomy of this section of the paper allows one to identify specific trajectories, with certain specializations in the SMES production process.

5.3 Innovative Efforts Results: SMEs' patterns

The analysis of innovative efforts employed in this section follows the work of De Marchi et al. (1996), which discusses the need for specific tools to measure the innovative efforts of small- and medium-sized enterprises that cannot be accounted for solely by the efforts incorporated in research and development.

The sources used by firms to create innovation, constitute an ensemble of variables that consider the efforts of each source applied. Therefore, one considers the relationship of the total expenditure in each activity, and the total sales revenue of each sector, as employed in the studies of Campos and Ruiz (2009) and Silva and Suzigan (2014) for Brazil's entire manufacturing industry.

The Calinski-Harabasz pseudo-F was used during the SME grouping process in the clusters analysis to provide statistical legitimacy to the partition, in which the R^2 confirms the statistical significance of the groups formed. The pseudo-F was 71.20, and was employed associated with a Duda/Hart Je(2)/Je(1) test that reached a value of 0.845, with a pseudo-T^2 of 5.42, which is considered significantly low.

The variables used in the analysis presented a considerably significant R-squared value of 92.42, according to Table 6. This table discloses the performance of the industries, already distributed in four clusters given the statistical partition simulation, in relation to the extent of innovation efforts.

Table 6 – SMEs cluster analysis: innovative efforts

Cluster	Sectors	Innovative Efforts: Internal R&D	Internal Product Design	Internal Training	Internal Mkt	External R&D	External Knowledge	M&E
	Brazil (Manufacturing Industry)	*0.22%*	*0.25%*	*0.09%*	*0.11%*	*0.02%*	*0.06%*	*1.78%*
1	Beverages	0.13%	0.15%	0.04%	0.06%	0.00%	0.02%	0.65%
	Apparel and Luxury Goods	0.05%	0.12%	0.04%	0.12%	0.04%	0.04%	1.07%
	Coke Production and Oil refining	0.12%	0.09%	0.02%	0.03%	0.00%	0.02%	1.52%
	Tobacco	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.59%
	Leather and Footwear	0.05%	0.05%	0.05%	0.14%	0.01%	0.03%	1.00%
	Instrumentation	0.04%	0.34%	0.22%	0.03%	0.00%	0.08%	0.75%
	Metallurgy	0.06%	0.06%	0.03%	0.02%	0.02%	0.02%	1.11%
	Food	0.07%	0.13%	0.02%	0.06%	0.00%	0.02%	1.45%
	Lumber	0.04%	0.08%	0.07%	0.05%	0.00%	0.06%	1.47%
	Non-Metallic Mineral Products	0.04%	0.28%	0.21%	0.05%	0.01%	0.02%	1.61%
	Cluster Average	*0.06%*	*0.13%*	*0.07%*	*0.06%*	*0.01%*	*0.03%*	*1.12%*
2	Rubber and Plastic	0.10%	0.32%	0.12%	0.09%	0.02%	0.04%	2.05%
	Paper and Forestry	0.02%	0.18%	0.04%	0.04%	0.01%	0.01%	2.24%
	Printing and Publishing	0.34%	0.17%	0.11%	0.08%	0.00%	0.19%	3.84%
	Other Industries	0.55%	0.43%	0.37%	0.39%	0.05%	0.13%	2.27%
	Machinery and Equipment	0.28%	0.25%	0.06%	0.12%	0.02%	0.07%	3.06%
	Furniture	0.08%	0.10%	0.07%	0.17%	0.02%	0.13%	2.17%
	Textiles	0.09%	0.11%	0.13%	0.07%	0.00%	0.01%	2.43%
	Metal Products	0.16%	0.29%	0.08%	0.07%	0.03%	0.05%	1.95%
	Motor Vehicles	0.26%	1.18%	0.04%	0.05%	0.05%	0.05%	2.75%
	Cluster Average	*0.21%*	*0.34%*	*0.11%*	*0.12%*	*0.02%*	*0.08%*	*2.53%*
3	Electronics Equipment/Internet and Communications Equipment	1.68%	0.37%	0.09%	0.25%	0.08%	0.14%	0.78%
	Cluster Average	*1.68%*	*0.37%*	*0.09%*	*0.25%*	*0.08%*	*0.14%*	*0.78%*
4	Transport Equipment	0.19%	0.23%	0.08%	1.27%	0.02%	0.01%	1.40%
	Electrical Equipment	0.48%	0.20%	0.34%	0.12%	0.02%	0.03%	1.60%
	Pharmaceuticals and Biotechnology	0.75%	0.55%	0.09%	0.83%	0.07%	0.06%	1.33%
	Chemicals	0.36%	0.16%	0.12%	0.10%	0.02%	0.13%	1.54%
	Cluster Average	*0.45%*	*0.28%*	*0.16%*	*0.58%*	*0.03%*	*0.06%*	*1.47%*

$R^2 = 0.9242$

Source: PINTEC 2008.

The taxonomic results for SMEs supported by innovation efforts are summarized in Table 7. Four clusters were identified, and clusters 3 and 4 disclose high technological dynamism, expressed in greater R&D efforts. This contrasts with cluster 1, which demonstrates low dynamism and high dependence on the acquisition of machinery and equipment (M&E).

Cluster 2 is in an average position, and presents high expenditures in M&E and low R&D, despite innovation efforts above the national average.

Table 7 – Summary characteristics of clusters in accordance to SMES innovation efforts – PINTEC 2008.

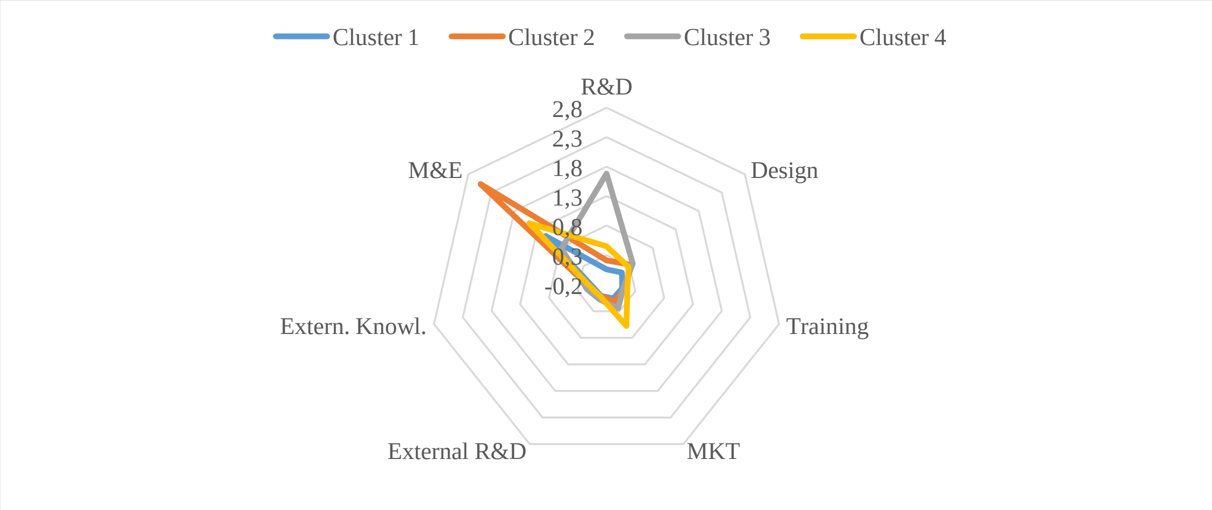
	Cluster 1	*Cluster* 2	*Cluster* 3	*Cluster* 4
Innovation/ Highlights	Low Innovative Efforts –below national average Low dynamism Acquisition of M&E at national average	Innovation efforts on average or above national average. High M&E associated with average R&D	High innovative efforts R&D 6x times national average Low Acquisition of M&E	High innovative efforts R&D 100% national average. Technological dynamism
Sectors	Apparel, Leather and Footwear, Lumber	Mass Production (Vehicles) and Traditionals	Electronics Eq.; Internet and Commun. Eq.	Chemical, Pharma/Biotech, Electrical Equipment

Figures 5 and 6 summarize the results for SMEs and large firms using dimensional graphs. Four clusters can be observed regarding small- and medium-sized enterprises, while six clusters are displayed for large firms, validating that these variables again possess significant behavioral variability.[5]

Clusters 3 and 4 demonstrate a science-based sectoral pattern of innovative efforts, based on Pavitt's taxonomy, for small- and medium-sized enterprises, and disclose a dissimilarity from others due to specificities in R&D expenditures. Similar innovative efforts were found in cluster 3 for larger firms. The lowest innovative efforts were found in cluster 1 for SMEs, and in clusters 2 and 4 for larger firms. Intermediate innovative efforts can be observed in cluster 2, for SMEs performing at the national average or above-average, but with a high dependence on the acquisition of machinery and equipment. Similar situations can be identified for larger firms in clusters 1 and 5, in which the dissimilarities include that group 1 has lower expenditures in M&E, while grouping 5 expends less in R&D.

[5] Cluster 6 for large firms identifies only the tobacco industry. This result requires further understanding, and suggests other specific investigative work that escapes the scope of this paper.

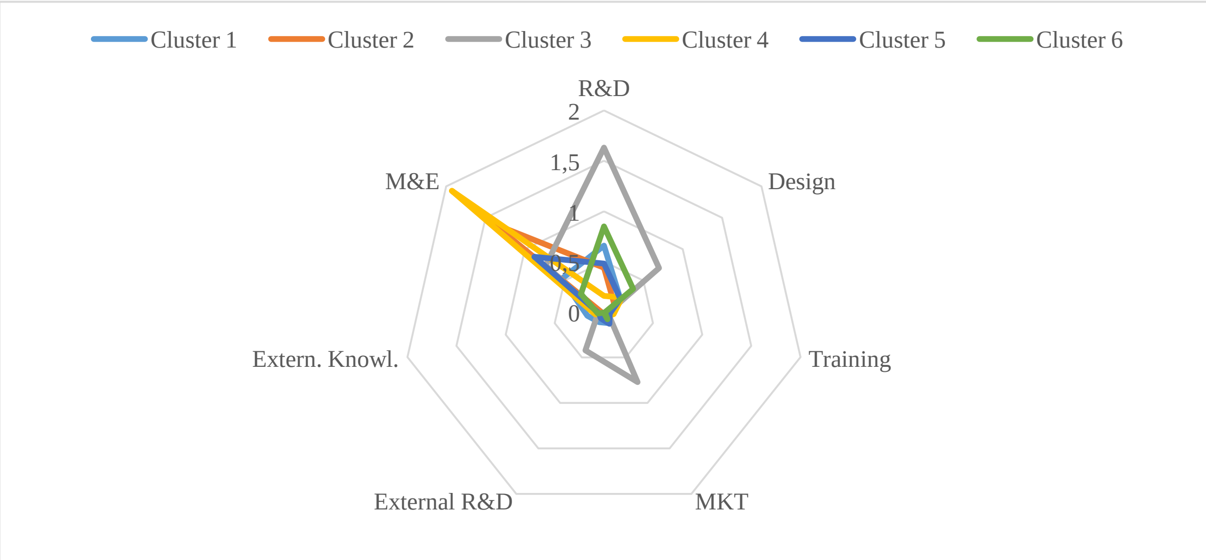
Figure 5 – Pattern dimensions* for innovative efforts - for SMEs



* Build based on clusters' averages.

Regarding small- and medium-sized enterprises, clusters 3 and 4 display a science-based sectoral pattern of innovative efforts, based on Pavitt's taxonomy, and disclose a dissimilarity from others due to specificities in R&D expenditures. Similar innovative efforts were found for larger firms in cluster 3. The lowest innovative efforts were found in cluster 1 for SMEs, and in groupings 2 and 4 for larger firms. Intermediate innovative efforts can be observed in cluster 2, for SMEs performing at the national average, or above average, but with a high dependence on the acquisition of machinery and equipment. Similar situations can be identified for larger firms in clusters 1 and 5, in which the dissimilarities include that grouping 1 has lower expenditures in M&E, while grouping 5 expends less in R&D.

Figure 6 - Patterns dimensions* for innovative efforts - for large firms



* Build based on clusters' averages.

6. Discussion and Concluding Remarks

6.1 Summary of main findings and implications for theory and practice

The taxonomy developed for SMEs, in summary, corroborates that the most in-house R&D intensive group, the science-based sectors, display the tendency to evolve, with intensity[6], other forms of innovative strategies. This conclusion also applies to larger firms. Many elements of technological trajectories were analyzed, and are exhibited in Table 8 in the Appendix, which summarizes the sectoral patterns of technological change for Brazilian manufacturing SMEs.

The supply-dominated pattern demonstrates low innovative efforts, presenting process innovation output with its primary knowledge source being external through the acquisition of machinery and equipment, in accordance with the studies of De Jong and Marsilli (2006). This pattern is similar to the findings of Pavitt (1984) with a certain presence of marketing. This paper posits that supply-dominated SMEs are more process innovative than product innovative, in terms of innovative output types, which is the same conclusion reached by De Jong and Marsili (2006). Furthermore, regarding the degree of innovation novelty, incremental innovation predominates, similar to results reported by Campos and Ruiz (2009).[7]

The scale-intensive patterns' innovation intensity is average. Similar results were obtained by De Jong and Marsili (2006) for SMEs' identical taxonomic pattern. Furthermore, findings indicate that innovation is originated externally, as well as both internally and externally. The resulting input type is more expressive in terms of process innovation than product innovation, but presents both types. This parallels the findings of De Jong and Marsili (2006), which reported this taxonomic pattern as possessing a mix of product and process innovation.

Scale-intensive firms display both incremental and incremental/radical innovation results. The industries that are denoted as "both" consist of sectors with radical product or process innovation above the national average, which proves of interest. According to Campos and Ruiz (2009), this pattern is characterized by product and process innovation results, radical or incremental in nature, similar to the results obtained by this study.

While specialized-suppliers demonstrate a medium-high to high technological intensity, corroborating the results of De Jong and Marsili (2006), they differ in respect to the primary innovative output, or what these authors consider "product innovation." According to this study, this pattern is predominantly a mix of product and process innovation, similar to the work of Campos and Ruiz (2009). The authors reported that this pattern, regarding the nature of innovation, presents a mix of incremental, and both incremental and radical, innovation similar to the findings of this study.

Finally, the science-based pattern revealed results similar to those obtained by De Jong and Marsili (2006), as well as Campos and Ruiz (2009), which indicates high innovative intensity with predominantly product innovation. The main source of innovation for science-

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[6] The intensity consists of the degree of technological dynamism, and refers to the position of the value of variables analyzed in the taxonomies in relation to the national average for SMEs. If this stays below the national average, it is considered low; if it remains in the middle, it is considered of average intensity; and if it stays far above average, the intensity is denoted as high. As there are three blocks of variables, these intensities constitute a synthesis of the obtained intensities.

[7] As highlighted previously, this study was conducted for the entire Brazilian manufacturing industry, without any size distinction.

based firms is R&D, but they also expend great innovative efforts in practically all innovative activities.

It is possible to identify similarities in the sectors' profiles for different degrees of groupings' dynamism by drawing comparisons between the resulting clusters for SMEs and large firms. The sectors to highlight in the more dynamic clusters, which congregate in science-based industries, are pharmaceuticals-biotechnology, electronics equipment-Internet and communications equipment, and chemicals for both sizes of firms.

Similarly, if clusters with fewer technological opportunities are analyzed, as in the industries that suit the supplier-dominated pattern, it is possible to verify that such sectors as lumber, textile, and apparel are representative of these groupings for small- and medium-sized enterprises and large firms.

The taxonomic analysis drawn throughout this study yields evidence that the Brazilian manufacturing enterprises analyzed fit with Pavitt's (1984) taxonomy. Furthermore, the composition of clusters reveals, through the intersection of studied characteristics, a consistent data aggregation.

6.2 Concluding remarks

The objective of this work was to develop a sectoral pattern analysis of Brazilian SMEs, with firm-level data, to explain the heterogeneity of small- and medium-sized enterprises in terms of the distinct configurations of their innovative activity.

The results obtained confirm the study hypothesis that sectoral firm dissimilarities, attributed to the categories of Pavitt's (1984) taxonomy, are valid for understanding Brazilian manufacturing SMEs' innovative activity, with a few adjustments for economic and firm reality adequacy.

The three groups of variables, used in blocks to analyze and build the taxonomy summary, allowed for the identification of specific industry characteristics. This confirmed that drawing sectoral patterns based upon innovative behavior is greatly influenced by technological sectoral trajectories, in which industries with higher technological dynamism are associated to indicators of higher levels of innovative activities, and also for SMEs.

Furthermore, the comparative analysis of large firms reported that the similarities are greater between SMEs and large firms than the dissimilarities, according to results obtained from the cluster analysis, indicating that the sectoral dynamics found are parameters for both firm sizes.

This study concludes that Brazilian industry's sectoral diversity is significant and cannot be neglected by industrial policies. Then "horizontal" and "vertical" policies are important to encompass these firms. The results were similar to those found by Campos and Ruiz (2009), who analyzed the sectoral diversity for Brazilian industrial companies.

It is important to consider limitations of this study. There are some important features and differences of innovative activities of the SMEs and the larger firms that were not analyzed in the paper. To carry out this task would be necessary to consider additional literature and extend the scope of the paper.

Finally, although the sectoral differences, this study does not allow systematic comparisons with similar studies carried out for other countries. The main differences are in the databases and in the methodologies.

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APPENDIX

Table 8 – Summary table: sectoral innovation patterns for SMEs - PINTEC-2008

Sectors	Innovation Input			Innovation Output	
	Internal/external	Intensity	Main Source	Product/process	Radical/Incremental
Supply Dominated Sectors					
Textiles	External	Low	M&E	Process	Incremental
Apparel	External	Low	Marketing/M&E	Process	Incremental
Leather and Footwear	External	Low	Marketing.	Process	Incremental
Lumber	External	Low	M&E	Process	Incremental
Rubber and Plastic	Both	Low	M&E/Design	Process	Incremental
Furniture	External	Low	M&E/Design	Process	Incremental
Other Industry	Both	Medium	Training/Marketing	Process	Incremental
Scale Intensive and Mass Production Sectors					
Food	External	Medium	M&E.	Process	Both
Beverage	Both	Medium	R&D/Design./M&E.	Process	Incremental
Printing and Publishing	Both	Medium	M&E/R&D.	Process	Incremental
Coke Production and Oil refining	Both	High	R&D/M&E	Process	Both
Non-Metallic Minerals Products	Both	Medium	M&E/Training/Design	Process	Incremental
Metal Products	Both	Medium	M&E/Design/R&D	Process	Both
Paper and Forestry	Both	Medium	M&E/Design	Process	Incremental
Tobacco	External	Medium	M&E	Product	Incremental
Metallurgy	Both	Medium	M&E/R&D/Design	Process	Incremental
Motor Vehicles	Both	Medium	M&E/Design/R&D	Process	Both
Specialized-Supplier Sectors					
Machinery and Equipment	Both	High	Design/R&D/M&E	Both	Both
Transport Equipment	Both	Med-High	Design/M&E/Marketing	Process	Both
Instrumentation	Internal	Med-High	Training/D&E	Process	Incremental
Science-Based Sectors					
Electronic Equipment/Internet and Communications Equipment	Both	High	P&D/Trein	Product	Both
Chemicals	Both	High	R&D/Ext.Knowl./M&E	Product	Both
Pharmaceuticals and biotechnology	Both	High	R&D/Design/Marketing	Both	Both
Electrical Equipment	Both	High	R&D/Training/M&E	Product	Both