Opportunity vs. complex learning processes: sectoral classification criteria based on technological regimes

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Introduction

Several contributions have showed that different industries exhibit different characteristics in terms of innovation, linkages with universities and research and development (R+D) centers, and capacity for technological diffusion through their relationship with other industries (Freeman et al., 1982; Geroski, 1991; Nelson and Winter, 1977). Literature has resorted to concepts as technological regimes (Malerba et al., 1997; Malerba and Orsenigo, 1997), sectoral systems of innovation (Malerba, 2002), technological trajectories (Dosi 1982), or sectoral patters (Dosi, 1982; Malerba and Orsenigo, 1997; Pavitt, 1984) in order to account for such differences. Since then, it has been proposed several sectorial taxonomies aimed to distinguished technological intensity of sectors in trade or productive specialization of developed countries (Archibugi and Michie, 1995; Castellacci, 2008; Hatzichronoglou, 1997; Lall et al., 2006; Marsili and Verspagen, 2002) y and developing (Katz and Stumpo, 2001; Lall, 2001; Petralia and Marin, 2015). According with this literature, there are differences among sectors regarding their capacity to innovate, self-transform on basis of technological change and being diffusers of innovations and new knowledge (Rosenberg, 1963). Therefore, the trade and productive specialization profile of countries can affect their dynamics of innovation, learning and technological change.

According to a Schumpeterian perspective, economic development and structural change are processes of qualitative transformation of a productive structure, which emanate from introduction of new products and processes, or, in other words, innovation and technological change. If sectors show differences in the way they learn, adopt and diffuse innovation, therefore, the productive and trade profile is not trivial on their effect on potential economic development.

Recently, some papers have minimized the relevance of sectorial differences and, although they are aware on the relationship between specialization profile and development, they also indicate that there are successful development strategies based on sectors traditionally classify as low R+D intensity or low technological dynamism, like strategies based on natural resources (Iizuka and Katz, 2010; Pérez, 2010; Petralia and Marin, 2015; REDSUR, 2014). The main argument of this works relies on the fact that technology opportunities, understood as the easiness of innovating for any given amount of resources invested in search (Malerba and Orsenigo, 1997), and measured as the efficacy of innovation activities expenditures are dependent of historical and productive context. Therefore, a new technological paradigm may offer new opportunities for traditional sectors. For example, new information and communication technologies or biotech industries has the potential to transform sectors in primary activities, like agriculture, opening them to new opportunities to innovate. In this regard, it is difficult to stablish which sectors are opener to introduce new knowledge and act as dynamic activities in technology diffusion.

Nevertheless, an approach exclusively focused on opportunity may hide how other attributes of technological regimes interplay with opportunity and may lead to a misleading impression of learning processes in sector dynamics. The concept of technological regimes (Malerba and Orsenigo, 1997) considers, besides opportunity, cumulativeness, appropriability and technological base. Considering these four attributes gives a more complex perspective of innovation, learning, and capacity building processes at sectorial level.

In this paper, we propose to analyze sectorial innovation profile of manufacture industry in Argentina. We followed Malerba and Orgsenigo (1997) technological regimes. We operationalized and estimated different indicators for innovation efforts, appropriation strategies and learning sources. Then, we applied a multilevel model to evaluate the differences among sector in the association between those indicators and the introduction of successful innovation. This exercise allowed us to estimate sectorial indicator for opportunity, appropriability, cumulativeness (learning based on experience) and technological base (learning based on interaction with universities or other firms).

A first observation that emerges from the results is that the different sectors show differences both in the efforts they make and in the degree to which they are associated with innovation results. While some sectors systematically show a greater relationship between their efforts and the introduction of innovations, others only show association in some indicators and in other cases the efforts do not seem to have a clear incidence. From this we can show that although the opportunity, understood as the association between R&D expenditure and innovation results, is present in a large number of sectors, even in traditional sectors, such as food or apparel. Other elements of technological regimes such as appropriability or cumulativeness, only appears in sectors frequently characterized as knowledge intensive. This could lead to propose that the opportunity is a more sensitive attribute to the technological and productive context than the rest. From the results obtained, we propose a sector taxonomy of the Argentine manufacturing industry in terms of the consistency between these four elements of the sectoral systems and the levels reached in the four indicators.

The rest of the article is organized as follows. In section 1 we present the conceptual framework, giving an account of the different contributions to the theme and positioning the contribution of Marlerba and Orsenigo, on which the proposed exercise is based. Some background of this work is discussed and the main hypotheses are presented. In section 2 we describe the proposed methodology, the data and the variables used. In section 3 we present the results of the multilevel models and the proposed taxonomy. In section 4 we discuss the results obtained from the comparison of the proposed taxonomy with other taxonomies proposed by the literature. Finally, in section 5 we present the main conclusions.

1. Sectoral differences acording to the literature

The starting point of this article is that firms belonging to different sectors have different innovative behavior. This is a stylized fact widely recognized by the literature on innovation and technological change. From the 1980s onwards, several papers argued that companies conduct different learning and innovation activities with different results when they are in different sectors. There are differences in: (i) the intensity of firms' search and learning activities, (ii) the efficiency of innovation expenses, understood as the relationship between those expenses, the innovations actually introduced and their impact on firm’s economic perform, and in (ii) firm’s management strategies regarding searching, learning and innovation and the monetary efforts made.

The sectoral differences are theoretically justified based on the assumptions made upon knowledge, information and learning. On one hand, there is the MAR tradition, as it is called (Glaeser et al. 1992), that collect Marshall (1920), Arrow (1962) and Romer (1986) contribution on knowledge. This tradition focuses on the qualities of knowledge as a public good and therefore on the problems of appropriation. In sectors with greater difficulties of appropriation, therefore, there will be a subinvestment in R&D unless public policies solve this market failure (for example, through intellectual property rights). Within this tradition, therefore, spillovers of knowledge are responsible for differential performance in innovation and technological change between sectors (Jaffe 1986), but also between regions (Audretsch and Feldman, 1996; Feldman, 1999) even between countries, as new economic geography stands (Krugman 1991; Krugman 1997).

On the other hand, the evolutionary and neoschumpeterian literature of innovation and technological change has pointed out some key issues in knowledge and learning far beyond appropriation. Among them there are that (i) knowledge is industry-specific and it depend on technological trajectories (Dosi et al., 1988; Nelson and Winter, 1982), (ii) firms are heterogeneous and have different capacities and routines (Richard R. Nelson y Winter 1982) upon wich they build their competitive advantages, and (iii) the way in which the firms build those ventages is idiosincratic but it is shaped by the sector they belong. Thus, firms’ competition in the market are firm- and sector-specific although both logics are intertwined. In this context, therefore, the sectoral differences in learning and competition processes define the possibilities of transforming the generated knowledge into competitive advantages and rents.

To address the sectoral differences in innovation, the evolutionary and neoschumpeterian literature coined the concepts of technological regimes and technological trajectories. The technological regime refers to the "set of properties of the technologies and characteristics of the learning process that are involved in innovation activities". These characteristics of each technology can be summarized in four attributes: opportunity, appropriability, accumulation and knowledge base. The attribute of opportunity refers to the ease to which innovations are obtained from a certain amount of resources. Therefore, it speaks of the effectiveness of innovation spending. The sectoral differences in this aspect refer to the degree of maturation of the technology (Utterback and Abernathy 1975) and to the type of knowledge involved (scientific, technological, markets or organizational). The appropriability attribute refers to the possibilities of capturing economic benefits of innovation. This means the possibilities of building competitive advantages based on learning processes, displacing market competitors, restricting copy and imitation and sustaining innovation rents. The authors argue that beyond the individual efforts undertaken, the characteristics of the knowledge involved (tacit or codified) and the type of innovations (product or process) affect these possibilities and those are sector-specific features. The attribute of cumulativeness refers to the degree to which learning processes are path dependent, forcing companies to continuously make learning and innovation efforts that also change sector by sector. Finally, the attribute of base of knowledge refers to the type of knowledge on which innovative activities are based. It refers to the nature of knowledge (generic or specific, tacit or codified, complex or simple, independent or systemic) and its mode of transmission, which is specific to the type of technology dominant in a sector.

These four attributes are combined in a specific way in the different sectors giving rise to specific industrial dynamics. The Schumpeter Mark I industrial dynamics (J.A. Schumpeter 1978) are those in which processes of creative destruction lead to high rate of entry and exit of firms. Firms enter the market and innovate with the intention of obtaining technological quasi-rents, displacing existing companies. But as appropriation and cumulativeness are low the quasi-rents are always transitory and the small companies and the competitive markets prevail. On the other hand, the Schumpeter Mark II industrial dynamic (J.A. Schumpeter 1994) highlights the importance of R&D departments of large firms consolidated in the industry as the main source of innovation. It is a creative accumulation in which the knowledge accumulated by large companies with market power constitutes a strong barrier of entry for the access of new competitors. Then, in these dynamics there is greater possibility of appropriation and accumulation is high.

The technological trajectories were defined by Pavitt (1984) based on a study of the technological interdependencies among the productive sectors. Pavitt analyzed whether, first, the technology used by a specific sector comes from within or is provided by other productive sectors. He studied the origin and destination of innovations from a patent analysis for the United Kingdom. Second, it analyzed the characteristics of these innovations and of companies involved, considering the sources of learning (intra- or extra-firm) and the nature of the technology produced in the sector (product or process), firm size and sector. Based on these criteria, Pavitt identified four categories of sectors. Fist, the intensive scale sectors, which have the possibility of taking advantage of economies of scale and those derived from an increasing division of labor. In this case, the sources of learning are internal, based on both experience and R&D departments, are sectors that allocate a significant part of their resources to technological supplies, although given the product's homogeneity, innovations are oriented to optimize production processes aiming to cost reduction. Second, the specialized supplier sectors are aimed at providing specialized products to a wide variety of sectors. Learning sources combine customer interaction with internal searches based on R&D. The innovations are oriented to the development of new products that involve improvements of processes for other sectors. Third, science-based sectors are characterized by their proximity to basic science in the development of new products and processes. They maintain strong interactions with universities or centers of science and technology that combine with their internal efforts to develop their innovations. The scope of application of its developments is varied, being able to provide technology to the rest of the productive sectors. And forth, dominated by suppliers sectors contribute little to the process of technical change since its main source of innovation incorporated in capital goods and inputs provide by other companies.

It is interesting to note that technological regimes (Marleba and Orsenigo, 1997) and technological trajectories (Pavitt, 1984) agree on the type of elements that identify as determinants of learning and innovation behavior at sectoral level. The sources of learning, the type of innovation, the product life cycle, the type of actors involved, among others, are all common factors. This leads to the proposed sectoral taxonomies showing a significant overlap (see table 1 in the annex), although what motivates them is essentially different in each case: industrial dynamics with a focus on competition processes (Malerba and Orsenigo) and technological interrelations among productive sectors, in the other case (Pavitt).

These taxonomies, based on a study of innovation processes, are complemented by other proposals for sectoral taxonomies, focused exclusively on the intensity of research and development activities, such as the sector taxonomy developed by the OECD (Hatzichronoglou, 1997) or the proposed by CEPAL (Katz and Stumpo, 2001) based on factorial intensity and the relation between this and technological dynamism.

All these studies agree that the different sectors have a specific and specific behavior in terms of technological learning and innovation and, despite some difference, a high correlation can be established between what they identify as sectors of high or low technological dynamism.

However, recent work has relativized the importance of sectoral differences in innovation and the relationship between specialization and development. Some authors (Leiponen and Drejer, 2007; Srholec and Verspagen, 2012) argue that differences in innovation efforts and results are more important between firms than between sectors. On the other hand, other authors have re-evaluate development strategies based on natural resources (Iizuka and Katz, 2010; Pérez, 2010; Petralia and Marin, 2015; REDSUR, 2014) arguing that technological opportunities, understood as efficiency in innovation costs (Malerba and Orsenigo 1997) are dependent on the historical and productive context. Thus, in developing countries such as Argentina, traditional or resource-intensive sectors can be much more effective in transforming their innovation efforts into new products and processes for national and international markets than sectors traditionally categorized as high- technology. In particular, within the current technological paradigm in which biotechnology extends the possibilities in structures based on natural resources.

In particular, Marin and Petralia's (2015) study of technological opportunities for Brazil and Argentina offers a sectorial taxonomy according to this attribute of technological regimes. This exercise allows them to show that the sectors that identify with high opportunity do not correspond to those traditionally classified as high technological dynamism and vice versa. On this basis they discuss the relevance of development policies aimed at the promotion of technologically dynamic sectors and propose that countries with specialization in traditional products have as much potential to pass economic development processes associated with innovation as those specialized in high technology industries.

On the other hand, the literature of global value chains has also called into question the taxonomies that group sectors according to their technological intensity. Within this perspective would not be the sectors but various activities transverse to them, such as quality or design, truly bearers of technological change (Gereffi et al., 2005; Milberg and Winkler, 2013). In terms of specialization and development, some authors argue that up-grading processes within global chains should be the focus of development strategies. The latter is leading to stop thinking of industrial policy in sectoral terms (BID, 2014) to guide them in strategies of international insertion and up-grading in global value chains (Giuliani, Pietrobelli, and Rabellotti 2005).

The objective of the article is to offer a sectorial taxonomy that describes the attributes of the sectors of the current Argentine manufacturing industry in terms of learning and innovation. In particular, we believe that sectoral attributes are relevant to the dynamics of learning and innovation and that there are sectoral differences in how efforts translate into successful market innovations. On the other hand, we understand that while technological opportunities may be present in sectors conventionally classified as traditional (Petralia and Marin 2015), in addition to the capacity to transform efforts into results, sectors may have a differential behavior in appropriability, Accumulation and knowledge base described by Malerba and Orsenigo (1997). For this reason, the proposed taxonomy considers these attributes as well. Finally, we also understand that the growing fragmentation of sectors in global production chains does not allow a linear and general interpretation of sectoral behavior. Therefore, the results obtained are evaluated considering the specificities adopted by the sectors in the local productive network.

2. Methodology and data

a. Methodology

In order to measure sectoral differences in innovation, we propose to estimate a set of multilevel models that allow us to differentiate the effect of firms' individual behaviors in terms of innovation and learning efforts on the effects of belonging to a sector on the success of innovation.

Multilevel models are used to study hierarchically structured data, ie where the units of analysis are stratified into groups containing them. Multilevel models are also known as mixed effects models because they include fixed and random effects. Fixed effects allow us to identify the relationship between variables independently of the group or class to which the observation belongs, while the random part of the model allows us to capture the particular effect of the class or group in the relation. In this way, the multilevel models, as opposed to the ordinary least squares models, allow to estimate constants and coefficients corresponding to each group or class. In addition, considering the nested structure of the data allows us to estimate standard errors with greater precision (Albright y Marinova 2010; Petralia y Marin 2015) since errors within each group are likely to be correlated.

In our case, observations (firms) are stratified according to their sectoral membership, since we are interested in identifying the particular effect of each branch of activity on the relationship between efforts and innovative success. We consider four types of innovative effort: spending on innovation activities, formal and informal strategies for appropriation of knowledge, links with science and technology institutions or other companies, and innovation efforts persistence. The estimation of the random coefficients by sector allows us to measure the capacity of each sector to transform each of these innovation and learning efforts into innovative success, that is, the sectoral attributes of opportunity, appropriability, knowledge base and accumulativity.

The use of multilevel models to estimate the opportunity of different sectors as the random part of the slope has already been proposed by (Petralia and Marin 2015). Our work complicates the results obtained by these authors taking into account the four attributes of sectoral regimes and not just opportunity.

Following (Albright and Marinova 2010), we consider first, an empty model, ie without independent variables, but allowing the constant to vary by branch of activity, to know the average innovative success per industry:

$$y_{ij} = \beta_{0j} + r_{ij} \tag{1}$$

Where the dependent variable y_{ij} (the innovative success of the firm i stratified in sector j) is equal to the average innovative success of branch j (β_{0j}) plus an error r_{ij} at the individual level. As there may be a general and a specific effect for each branch, the intercept can be decomposed as follows:

$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{2}$$

Where γ_{00} is the average innovative success (general or fixed constant) and u_{0j} is a branch-specific effect (constant for each branch). Replacing 2 in 1 we get:

$$y_{ij} = \gamma_{00} + u_{0j} + r_{ij} \tag{3}$$

By including the vector of independent variables that explain the innovative success (in our case would be the efforts of innovation and learning) to equation 3 we obtain [1]:

$$y_{ij} = \gamma_{00} + u_{0j} + BX_{ij} + r_{ij} \tag{4}$$

If the effect of independent variables on innovation success is allowed to change by branch, then the slope vector could be decomposed into a fixed part and a variable according to sector:

$$B = G_0 + U_j \tag{5}$$

Then, replacing 5 in 4 we obtain the complete model with intercept and variable slope:

$$y_{ij} = \gamma_{00} + u_{0j} + G_0 X_{ij} + U_j X_{ij} + r_{ij} \tag{6}$$

The results of interest for the proposed exercise refer to the random components of the equation. On the one hand, u_{0j} will be indicated by differences in the level of innovative success between sectors, while the U_j vectors (one for each independent variable) will indicate the sectorial differences in terms of: opportunity, appropriability, knowledge base and accumulation.

Finally, to evaluate the importance of the analysis at the sector level, it is useful to estimate the intra-class correlation coefficient, which indicates the proportion of variability attributable to differences between classes (ie between sectors).

We call σ^2 to the variance of r_{ij} and we call σ_u^2 to the variance of u_j (that is, the sum of the variability of the constant per branch u_{0j} plus that of the coefficients that accompany the U_j independent variables). Thus, the proportion of the variation of innovative success attributable to the characteristics of the branch is obtained by:

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma^2} \tag{7}$$

If ρ is the intra-class correlation coefficient (Albright and Marinova 2010), then, the proportion of the variation attributable to the enterprise level would be $1 - \rho$.

[1] Note that the use of capital letters indicates vectors whereas the lowercase letters refer to scalars.

b. Data

The data were used for this work is provided by the ENDEI (Employment and Innovation Survey), jointly conducted by the Ministry of Labor, Employment and Social Security and the Ministry of Science, Technology and Productive Innovation. The database contains 3691 observations of manufacturing companies, with quantitative information of the company (mainly data on economic performance) and of productive activities and innovation. This database allows cross-section analysis since, although for some variables such as income, expenses and added value, information is available for the years 2010, 2011 and 2012, for the rest of the variables a single data item is available for each firm.

The survey is representative by size and branch of activity to two digits of ISIC Rev. 3 and four digits for selected branches such as Food, Chemicals, Machinery and Equipment and Automotive. For example, the Food branch is subdivided into Meat, Dairy Products, Wines and other fermented beverages and other foods. The same applies to the other three branches in which the survey includes subdivisions. The branch classified as "Other" includes the following ISIC Rev. 3 branches for which the sample selected is not representative: Manufacture of tobacco products, manufacture of coke, refining products of petroleum and nuclear fuel, Manufacture of motor vehicles and recycling.

The proposed exercise requires circumscribing the analysis to the firms that carried out innovation activities, since the questions related to innovation results were made to companies that had declared innovation efforts. This leads us to discard around 1000 observations for which no information on innovation results is available. Some comments were also discarded because they presented extreme values in the expenses of innovation on sales as of productivity (both variables used in the models).

c. Variables

In our analysis the dependent variable is the degree of success in the innovative performance of the firm, which we characterize as the competitive success that the company achieves from the innovation, ie if the innovation allowed the company to access new markets (national or international). We use two variables to represent this aspect. On the one hand, *nuemer* is a discrete ordered variable that assumes value 0 if the company does not accede to new markets from the innovation, 1 if it accedes to new national markets and 2 if accedes to new external markets. On the other hand, *nueext* is a binary variable that assumes value 1 if the company accedes to new external markets from the innovation and 0 otherwise. These indicators of the firm's innovative performance have the advantage of depending less on the subjectivity of the respondent than other indicators, such as innovation results (whether the company introduced new products or processes), the degree of novelty of innovation (if the innovation introduced is considered new for the firm, for the local market or for the international market) or the weight of the new products in sales (that is constraint to product innovation).

As independent variables of interest, we include indicators that characterize firms' innovation and learning efforts. The intensity of innovation is represented by the continuous variable *ainno*, which is the proportion that represents the expenditure in innovation activities of the company in its total revenues, average between the years 2010 to 2012. The estimated random coefficients for the variable *ainno* are indicators of sectoral differences of opportunity.

The protection of the innovation results achieved is represented by two binary variables that synthesize the different efforts made by the companies to protect the rents generated by the innovations obtained. The ENDEI reports whether the company performs 6 types of informal protection efforts (first reaching the market, active communication with customers, control of distribution and sales networks, keeping key technological issues secret, exclusive access to input and a larger scale of production) and 8 formal ones (industrial design, trademarks, utility model, copyright or breeder, signature of contracts of confidentiality with the personnel, signature of exclusive contracts with clients and patents). In order to synthesize the protection efforts, we performed a principal component analysis that allowed us to classify companies into 3 clusters according to: (i) whether they perform appropriation strategies combining formal and informal efforts, (ii) if they only perform informal efforts, and (iii) if they do not carry out protection efforts. From these clusters we construct two binary variables: first, *feiprot* that assumes value 1 for the companies that make efforts of formal and informal protection and second, *infprot* that assumes value 1 for the companies that only perform informal protection efforts. The estimated random coefficients for these variables are our indicators of the differences in appropriability between sectors.

The linkages for innovation are measured by two dimensions: scientific links, which refer to the company's links with universities and scientific and technical institutions, and technical links, which refer to links with suppliers and customers. The binary variable *vincyt* assumes value 1 if the company is linked to public and private universities and public institutions of science and technology for R&D, technological exchange, testing and testing, development or improvement or industrial design. The binary variable *vinemp* assumes value 1 if the company links with other companies to carry out activities such as training, technological exchange, testing and testing, development or improvement or industrial development. The estimated random coefficients for these variables are our indicators of sectoral differences of knowledge base.

Persistence is represented by the continuity of the company's innovation efforts. To measure persistence we construct the binary variable *pers* that assumes value 1 if the company makes internal R&D efforts in each of the three years covered by ENDEI, from 2010 to 2012, and 0 otherwise. In this case, the estimated random coefficient is an indicator of cumulative differences between sectors.

Among independent control variables we include the size of the company, the ownership of capital and productivity. The variable *Tam_nue* is a discrete variable that is included in the ENDEI and takes value 1 if the company is "Small-sized" (10 to 25 employees), 2 if it is "Medium-sized" (26 to 99) and 3 if it is "Large-sized" (100 or more). From *Tam_nue*, we construct two dummies variables to indicate if the company is medium or large. The property of capital is indicated by the binary variable *ext* which assumes value 1 if part of the capital of the company is foreign-owned. Finally, to measure productivity, we use the value added per worker reported by ENDEI for the years 2010 to 2012. We deflated the value added by Producer Price Index corresponding to each branch reported by the INDEC, which was increased according to a Consumer Price Index based on data from statistical institutes in 7 provinces. The continuous variable *vadeftra* is the aggregate value deflated by average worker for the years 2010 to 2012[2].

In Table 1 we present basic descriptive statistics for the variables we use in our empirical analysis.

Tabla 1 – Descriptive statistics.

Variable	Obs.	Mean	SD	Min.	Max.
nuemer	*2435*	0.57	0.76	0	2
nueext	*2435*	0.17	0.37	0	1
ainno	*2424*	0.03	0.04	0	0.41
vincyt	*2435*	0.29	0.45	0	1
vinemp	*2435*	0.39	0.49	0	1.00
infprot	*2435*	0.48	0.50	0	1
feiprot	*2435*	0.15	0.36	0	1.00
pers	*2435*	0.34	0.47	0	1
Tam_*nue*	*2435*	1.92	0.78	1	3
ext	*2435*	0.12	0.32	0	1
vadeftra	*2172*	173100.10	215922.60	214.57	2770411

Source: own elaboration based on ENDEI.

[2] Excluding observations with extreme vales by branch of activity, about 300 observations where dismissed.

In Table 2 we present the sectoral averages of the variables we use. It is interesting to compare the means of each sector for the two alternatives of dependent variable that we consider in this work. Although the means of these variables are not directly comparable because the *nuemer* variable (access to new markets from innovation) has three levels and *nueext* (access to external markets from innovation) only two, we can compare the ordering of sectors in terms of the averages of these variables. In this regard, we note that some sectors have relatively better innovative performance to access new markets than to access new export markets, such as car bodies, trailers and semi-trailers; leather and furniture. And on the contrary, some sectors present better relative performance in the variable *nuext* than in the *nuemer* variable, such as medical instruments, textile products and other transport equipment. Regarding the mean of variables that represent the innovation efforts, we also find that the sectors differs significantly.

Table 2 – Averages by sectors

Sectors	Dependent variables		Independent variables								
			Interest variables						Control variables		
	nuemer	nueext	ainno	vincyt	vinemp	infprot	feiprot	pers	Tam_nue	ext	vadeftra
Food	0.545	0.167	0.029	0.211	0.421	0.459	0.144	0.273	2.110	0.100	168134
Textiles	0.475	0.136	0.028	0.271	0.322	0.551	0.042	0.178	2.297	0.068	158958
Aparell	0.319	0.029	0.013	0.058	0.188	0.464	0.116	0.130	1.725	0.000	119182
Leader	0.663	0.150	0.026	0.138	0.363	0.575	0.125	0.313	1.888	0.075	108703
Wood	0.328	0.030	0.029	0.209	0.328	0.507	0.030	0.134	1.746	0.000	108225
Paper	0.538	0.115	0.027	0.269	0.410	0.577	0.141	0.154	1.846	0.115	152436
Edition	0.493	0.080	0.033	0.107	0.320	0.347	0.147	0.187	1.773	0.120	150416
Chemicals	0.674	0.215	0.024	0.417	0.403	0.472	0.229	0.569	2.097	0.278	250192
Rubber and plastics.	0.609	0.188	0.035	0.355	0.435	0.471	0.181	0.341	2.080	0.109	151335
Other min. no metalics.	0.404	0.079	0.033	0.360	0.326	0.573	0.146	0.393	1.888	0.169	116814
Metals	0.582	0.127	0.027	0.278	0.405	0.392	0.063	0.278	1.886	0.127	287184
Other metal products	0.527	0.147	0.031	0.273	0.407	0.493	0.100	0.307	1.973	0.073	144493
Machinery and eq.	0.675	0.265	0.028	0.313	0.434	0.470	0.133	0.458	1.783	0.157	168265
Medical devices	0.508	0.213	0.037	0.508	0.508	0.443	0.279	0.492	1.525	0.082	143090
Other transport eq.	0.457	0.130	0.029	0.370	0.413	0.261	0.239	0.326	1.739	0.000	248486
Furniture	0.600	0.093	0.036	0.173	0.347	0.493	0.173	0.293	1.693	0.027	110878
Machine tools.	0.723	0.277	0.034	0.255	0.436	0.511	0.128	0.511	1.723	0.106	147340
Meat	0.510	0.127	0.019	0.176	0.343	0.431	0.078	0.196	2.304	0.078	229846
Dairy products	0.412	0.087	0.032	0.225	0.313	0.538	0.112	0.262	1.925	0.075	157091
Wines	0.855	0.355	0.041	0.211	0.316	0.408	0.158	0.197	1.816	0.237	195105
Pharmaceutical	0.664	0.250	0.036	0.500	0.422	0.362	0.345	0.569	1.897	0.155	224391
Agro Machines.	0.857	0.304	0.028	0.304	0.286	0.589	0.107	0.464	1.554	0.054	133081
Househod appliances	0.467	0.100	0.027	0.333	0.467	0.617	0.200	0.433	1.667	0.083	138730
Electric, radio and tv.	0.654	0.192	0.028	0.413	0.404	0.510	0.135	0.442	1.837	0.087	200461
Body cars, trailers and semi-trailers.	0.679	0.143	0.017	0.536	0.357	0.536	0.143	0.500	2.143	0.179	184550
Autoparts	0.537	0.147	0.030	0.316	0.495	0.558	0.126	0.411	1.800	0.168	126027
Other	0.587	0.206	0.026	0.397	0.492	0.286	0.175	0.349	2.254	0.317	361147

Source: own elaboration based on ENDEI.

In Table 3 we present the correlation matrix. It should be noted that the higher correlations are observed between the dependent variables and between the dependent variables and the independent variables of interest. The lower correlation between the variables related to the innovation and learning efforts shows that the different indicators point to different aspects of the process and, therefore, their inclusion in the model becomes relevant.

Tabla 3 – Correlation matrix

	Dependent variables		Independent variables								
			Interest variables						Var. de control		
	nuemer	**nueext**	**ainno**	**vincyt**	**vinemp**	**infprot**	**feiprot**	**pers**	**Tam_nue**	**ext**	**vadeftra**
nuemer	1.00										
nueext	0,8382	1.00									
ainno	0,1034	0,0908	1.00								
vincyt	0,1635	0,1899	0,0314	1.00							
vinemp	0,1552	0,1503	0,0767	0,1872	1.00						
infprot	0,1229	0,0435	0,0078	0,0119	0,0638	1.00					
feiprot	0,1949	0,1981	0,0558	0,2357	0,1117	-0,3937	1.00				
pers	0,1363	0,1489	0,1176	0,1912	0,1062	0,0159	0,179	1.00			
Tam_nue	0,0285	0,1017	-0,1389	0,1507	0,092	-0,059	0,1192	0,0609	1.00		
ext	-0,0057	0,0583	-0,0198	0,0792	0,0604	-0,0544	0,0966	0,0511	0,2949	1.00	
vadeftra	0,0222	0,046	-0,0558	0,04	0,0303	-0,0571	0,0752	0,0265	0,1279	0,2036	1.00

Source: own elaboration based on ENDEI.

3. Results

The results of the proposed econometric exercise are presented in this section. The generic specification of the estimated models can be obtained by replacing in equation 6 the X_{ij} independent variables by the proposed variables (both interest and control).

If we incorporate the independent variables, but allow only the constant to be random, the equation of the model is defined:

$$\begin{aligned} y_{ij} = \gamma_{00} + \gamma_{10} ainno_{ij} + \gamma_{20} infprot_{ij} + \gamma_{30} feiprot_{ij} + \gamma_{40} pers_{ij} + \gamma_{50} vincyt_{ij} + \gamma_{60} vinemp_{ij} \\ + \gamma_{70} Tam\_nue\_mediana_{ij} + \gamma_{80} Tam\_nue\_grande_{ij} + \gamma_{90} ext_{ij} \\ + \gamma_{10\,0} vadeftra_{ij} + u_{0j} + r_{ij} \end{aligned} \tag{8}$$

Where y_{ij}, innovative success, is measured by both *nuemer* and *nueext* and the variables *Tam_nue_mediana* and *Tam_nue_grande* are dichotomous variables created from the variable *Tam_nue* for the medium- and large-sized companies, respectively.

If we add random effects for the causal variables of interest, the equation of the model is as follows:

$$\begin{aligned} y_{ij} = \gamma_{00} + \gamma_{10} ainno_{ij} + \gamma_{20} infprot_{ij} + \gamma_{30} feiprot_{ij} + \gamma_{40} pers_{ij} + \gamma_{50} vincyt_{ij} + \gamma_{60} vinemp_{ij} \\ + \gamma_{70} Tam\_nue\_mediana_{ij} + \gamma_{80} Tam\_nue\_grande_{ij} + \gamma_{90} ext_{ij} \\ + \gamma_{10\,0} vadeftra_{ij} + u_{0j} + u_{1j} ainno_{ij} + u_{2j} infprot_{ij} + u_{3j} feiprot_{ij} \\ + u_{4j} pers_{ij} + u_{5j} vincyt_{ij} + u_{6j} vinemp_{ij} + r_{ij} \end{aligned} \tag{9}$$

The terms with coefficients symbolized with γ correspond to the fixed effects and the terms with coefficients symbolized with u correspond to the random effects.

The results are presented in the following order. First, we analyze the results referred to the fixed part of the multilevel regressions. For that, we present 3 different specifications: (i) the empty model, (ii) the model with random constants by sector, and (iii) the model with random constants and coefficients by sector. This allows us to see the relevance of the selected indicators referred to the attributes of the sectoral regimes to explain the innovative success.

Second, we analyze the random part of the models. First, we present the differences in the constants by sector, in that way we take into consideration the starting point of each sector in terms of innovative success. Second, we show the sectorial differences in the coefficients corresponding to each type of effort, which, as explained above, allows us to approach the analysis of sectoral differences in terms of opportunity, appropriability, knowledge base and cumulativity.

Finally, with the information generated, we propose a sectorial taxonomy in terms of the coherence between the attributes of the sectoral regimes in the different branches of the Argentine manufacturing industry.

a. Fixed part of multilevel regretion

Table 4 presents the results of the multilevel models (constants and fixed coefficients). The first three columns show the results for models where access to new markets (national or international) is the dependent variable, and in the last three columns show the results where access to international markets is the dependent variable.

A first issue that can be seen in Table 4 is that the selected indicators on the attributes of sectoral innovation regimes were significant and positive in explaining innovative success in their two definitions[3].

The second observation refers to changes in both, constant and coefficients between the different specifications. By adding the variables referred to the attributes of the regimes and the controls the constant is reduced, which shows that the variables selected are relevant to explain the innovative success. On the other hand, allowing varying coefficients by branch of activity also changes in the fixed coefficients are observed, which shows that among productive sectors the selected attributes have a particular impact.

The importance of branches to explain variability in innovative success can also be seen in intra-class correlation (see Equation 7). If the intra-class correlation approaches zero, it means that sectoral differences in terms of both coefficients and constants are not useful in explaining innovative success. If, on the contrary, the intra-class correlation is closer to one means that sectoral differences are determinant. In the estimated models the intra-class correlation is 0.63 in the model that explains the innovative success from the access to new markets (national and international) and 0.84 in the case that explains it from the access to international markets by the introduction of an innovation.

[3] Since attributes are measured in different units and since there are strong correlations between some of the variables (see Table 3) it is not convenient to compare the values of the coefficients with each other.

Tabla 4 – Models estimates

Independent variables	Dependent Variables					
	nuemer			nueext		
	Empty model with random cons. [1]	Random cons. only [2]	Random coef. and cons. [3]	Empty model with random cons. [4]	Random cons. only [5]	Random coef. and cons. [6]
ainno		1,565***	1,616***		0,723***	0,735***
		(0,452)	(0,493)		(0,223)	(0,280)
vincyt		0,132***	0,132***		0,0834***	0,0831***
		(0,0363)	(0,0361)		(0,0179)	(0,0178)
vinemp		0,144***	0,140***		0,0643***	0,0623***
		(0,0325)	(0,0338)		(0,0160)	(0,0167)
infprot		0,317***	0,321***		0,0849***	0,0830***
		(0,0338)	(0,0432)		(0,0167)	(0,0211)
feiprot		0,514***	0,509***		0,193***	0,190***
		(0,0505)	(0,0502)		(0,0248)	(0,0257)
pers		0,0916***	0,0881**		0,0516***	0,0460**
		(0,0339)	(0,0366)		(0,0167)	(0,0198)
Tam_nue = 2, Mediana		0,0198	0,0224		0,0437**	0,0445**
		(0,0364)	(0,0363)		(0,0179)	(0,0179)
Tam_nue = 3, Grande		0,0170	0,0196		0,0659***	0,0683***
		(0,0435)	(0,0432)		(0,0215)	(0,0213)
ext		-0,103*	-0,0906*		-0,000684	0,00550
		(0,0536)	(0,0533)		(0,0264)	(0,0262)
vadeftra		5,21e-08	5,13e-08		3,42e-08	3,80e-08
		(7,34e-08)	(7,27e-08)		(3,62e-08)	(3,58e-08)
constante	0,568***	0,164***	0,162***	0,162***	-0,0332	-0,0340*
	(0,0240)	(0,0434)	(0,0392)	(0,0149)	(0,0224)	(0,0192)
Obs.	2435	2169	2169	2435	2169	2169

SD between brackets.

*** p<0.01, ** p<0.05, * p<0.1
Source: own elaboration based on ENDEI.

b. Multilevel models random part

Next, we present the results referred to the random part (constant and coefficients) of the multilevel models. Table 5 shows the constants per branch that arise from the analysis for the 6 different specifications of the model, ie the fixed constant plus the random constant of each branch (the sum of $\gamma_{00}\ y\ u_{0j}$ in equation 6). Tables 6 and 7 present the coefficients per branch of the different attributes of the sectoral regime, corresponding to specifications 3 and 6, which are allowed to vary. These coefficients were estimated as the sum of the general (fixed) coefficients and the specific (random) coefficients for each branch. ($G_0\ y\ U_j$ in equation 6).

Regarding to the constants per branch (Table 5), the following can be observed. First, the level of the sectoral constants is reduced by moving from the specifications of empty model to model with random constant and to the model with constant and random coefficients. These results are derived from the fact that the general constant is the one that is reduced with this passage. Which means that the variables used, as well as the variability of the coefficients that accompany them, improve the explanation of innovative success.

Second, the variability (standard deviation) of the constants is also reduced especially when moving from the models with only the random constant to the models with constant and random coefficients (from 2 to 3 for new markets and 5 and 6 for new external markets). This is explained by the fact that allowing the coefficients of the attributes to change at the sectoral level explains the greater part of the sectoral differences. In other words, the sectors are essentially differentiated by the specific contribution each attribute has to innovative success. In the particular case of model 6 this is very noticeable since the sectoral differences in the constant are annulled.

Third, some additional comments on the differences in the sectors themselves can be made. If we consider the model empty, the different constants per branch refer to the differences in the dependent variables per branch. In this context, we can see that in the models for both dependent variables the sectors that lead the ranking are wine and other fermented beverages, agricultural and forestry machinery, machinery and tools in general, chemical products and pharmaceuticals. At the other end are confections, wood, other nonmetallic minerals and dairy products. On the other hand, some sectors lose several positions by moving from the variable of innovative success measured as access to new markets or measured as access to international markets, including leather and furniture, while others gain places, such as medical instruments and other equipment. transport.

Table 5 – Constants by sector

Sectors	Dependent Variables					
	nuemer			nueext		
	Empty model with random cons. [1]	Sólo cons. aleatoria [2]	Empty model with random cons. [1]	Modelo vacío con cons. aleatoria [4]	Empty model with random cons. [1]	Coef. y cons. aleatorias [6]
Food	0.5509	0.1510	0.1652	0.1668	-0.0276	-0.0340
Textiles	0.5079	0.1590	0.1585	0.1411	-0.0305	-0.0340
Aparell	0.4400	0.0904	0.1541	0.0703	-0.0779	-0.0340
Leader	0.6202	0.2507	0.1672	0.1534	-0.0271	-0.0340
Wood	0.4467	0.0808	0.1558	0.0717	-0.0846	-0.0340
Paper	0.5520	0.1326	0.1602	0.1287	-0.0606	-0.0340
Edition	0.5282	0.1705	0.1651	0.1040	-0.0586	-0.0340
Chemicals	0.6408	0.1820	0.1601	0.2059	-0.0174	-0.0340
Rubber and plastics.	0.5957	0.1708	0.1634	0.1836	-0.0301	-0.0340
Other min. no metalics.	0.4738	0.0340	0.1544	0.1002	-0.1027	-0.0340
Metals	0.5760	0.2436	0.1666	0.1366	-0.0332	-0.0340
Other metal products	0.5393	0.1433	0.1621	0.1493	-0.0398	-0.0340
Machinery and eq.	0.6279	0.2263	0.1639	0.2371	0.0406	-0.0340
Medical devices	0.5392	0.0512	0.1543	0.1960	-0.0393	-0.0340
Other transport eq.	0.5221	0.1194	0.1584	0.1432	-0.0537	-0.0340
Furniture	0.5853	0.1627	0.1616	0.1135	-0.0738	-0.0340
Machine tools.	0.6599	0.2385	0.1644	0.2482	0.0425	-0.0340
Meat	0.5326	0.1574	0.1598	0.1356	-0.0552	-0.0340
Dairy products	0.4825	0.0960	0.1587	0.1084	-0.0733	-0.0340
Wines	0.7228	0.3784	0.1737	0.2994	0.1250	-0.0340
Pharmaceutical	0.6294	0.1685	0.1626	0.2315	-0.0003	-0.0340
Agro Machines.	0.7018	0.3058	0.1686	0.2532	0.0541	-0.0340
Househod appliances	0.5196	0.0741	0.1570	0.1212	-0.0863	-0.0340
Electric, radio and tv.	0.6209	0.1676	0.1618	0.1854	-0.0397	-0.0340
Body cars, trailers and semi-trailers.	0.6014	0.1993	0.1639	0.1530	-0.0527	-0.0340
Autoparts	0.5496	0.1192	0.1581	0.1510	-0.0532	-0.0340
Other	0.5776	0.1575	0.1621	0.1918	-0.0408	-0.0340

Source: own elaboration based on ENDEI.

Tables 6 and 7 present the levels of the coefficients of the different attributes of sectoral innovation regimes in the different productive sectors. In Table 6 are those referring to the model that estimates innovative success as access to new markets (national and international) and in Table 7 those who estimate it from access to international markets.

Table 6 – Slopes by sector. Model [3]

Sector	Variable independiente					
	ainno	*vincyt*	*vinemp*	*infprot*	*feiprot*	*pers*
Food	1.5726	0.1318	0.1672	0.2016	0.5087	0.0954
Textiles	1.4092	0.1318	0.1383	0.3750	0.5087	0.0834
Aparell	1.4653	0.1318	0.1406	0.3291	0.5087	0.0776
Leader	1.9273	0.1318	0.1556	0.4044	0.5087	0.0798
Wood	1.2060	0.1318	0.1284	0.2566	0.5087	0.0635
Paper	1.1326	0.1318	0.1439	0.2873	0.5087	0.0698
Edition	1.2893	0.1318	0.1342	0.2252	0.5087	0.0958
Chemicals	1.8075	0.1318	0.1343	0.4043	0.5087	0.0837
Rubber and plastics.	1.5638	0.1318	0.1434	0.2961	0.5087	0.0980
Other min. no metalics.	1.3426	0.1318	0.1181	0.1818	0.5087	0.0395
Metals	2.0718	0.1318	0.1573	0.4273	0.5087	0.0733
Other metal products	2.2156	0.1318	0.1493	0.2207	0.5087	0.0671
Machinery and eq.	2.3098	0.1318	0.1611	0.3377	0.5087	0.1558
Medical devices	1.9190	0.1318	0.1291	0.1835	0.5087	0.0606
Other transport eq.	1.5404	0.1318	0.1362	0.3245	0.5087	0.0572
Furniture	1.4318	0.1318	0.1403	0.3358	0.5087	0.0751
Machine tools.	1.6742	0.1318	0.1359	0.4076	0.5087	0.1506
Meat	1.2527	0.1318	0.1408	0.3639	0.5087	0.0854
Dairy products	1.2008	0.1318	0.1449	0.2024	0.5087	0.0789
Wines	2.4236	0.1318	0.1591	0.6417	0.5087	0.0920
Pharmaceutical	1.4973	0.1318	0.1411	0.3120	0.5087	0.0936
Agro Machines.	2.1564	0.1318	0.1361	0.4661	0.5087	0.1577
Househod appliances	1.2566	0.1318	0.1184	0.2278	0.5087	0.0758
Electric, radio and tv.	1.9849	0.1318	0.1515	0.2729	0.5087	0.1156
Body cars, trailers and semi-trailers.	1.6769	0.1318	0.1369	0.3427	0.5087	0.0818
Autoparts	1.0873	0.1318	0.1076	0.3216	0.5087	0.0993
Other	1.2056	0.1318	0.1200	0.3265	0.5087	0.0737

Source: own elaboration based on ENDEI.

Table 6 shows that the coefficients of two attributes do not show significant differences between sectors (scientific knowledge base and formal and informal appropriation). For the rest of the cases there are strong differences. On the other hand, although sector rankings according to attributes show correlation (that is, sectors with high opportunity tend to coincide with those with high appropriability, cumulativeness and knowledge base), in some cases there are notable differences, which would lead us to think that learning strategies and building knowledge-based competitive advantages change across sectors. For example, the food sector shows a medium opportunity, but a high technological knowledge base and high cumulativity, the medical instruments sector stands out only for high opportunity and the sectors of wines and leathers that rank well in all attributes except cumulative.

Table 7 – Slopes by sector. Model [6]

Sector	Independent variables					
	ainno	*vincyt*	*vinemp*	*infprot*	*feiprot*	*pers*
Food	0.7165	0.0831	0.0790	0.0529	0.1848	0.0806
Textiles	0.8207	0.0831	0.0630	0.1014	0.1872	0.0582
Aparell	0.5046	0.0831	0.0647	0.0607	0.1761	0.0213
Leader	1.0676	0.0831	0.0641	0.0813	0.1910	0.0367
Wood	0.0719	0.0831	0.0550	0.0539	0.1863	0.0235
Paper	0.2738	0.0831	0.0696	0.0726	0.1882	0.0286
Edition	0.1309	0.0831	0.0561	0.0252	0.1926	0.0384
Chemicals	0.7977	0.0831	0.0573	0.1203	0.1935	0.0463
Rubber and plastics.	0.7581	0.0831	0.0668	0.0659	0.1945	0.0577
Other min. no metalics.	0.3046	0.0831	0.0529	0.0318	0.1880	0.0046
Metals	1.0975	0.0831	0.0666	0.0786	0.1821	0.0071
Other metal products	1.0798	0.0831	0.0506	0.0648	0.2070	0.0346
Machinery and eq.	1.7058	0.0831	0.0772	0.1258	0.2010	0.1037
Medical devices	1.4910	0.0831	0.0597	0.0456	0.2016	0.0441
Other transport eq.	0.5723	0.0831	0.0604	0.0673	0.1975	0.0231
Furniture	0.1792	0.0831	0.0647	0.0757	0.1777	0.0412
Machine tools.	0.9974	0.0831	0.0639	0.1468	0.1929	0.1210
Meat	0.3584	0.0831	0.0605	0.0686	0.1819	0.0138
Dairy products	-0.1152	0.0831	0.0625	0.0563	0.1867	0.0371
Wines	2.0477	0.0831	0.0731	0.2628	0.2105	0.0637
Pharmaceutical	0.8381	0.0831	0.0648	0.0948	0.1946	0.0756
Agro Machines.	1.2184	0.0831	0.0625	0.1486	0.1992	0.1022
Househod appliances	0.5576	0.0831	0.0522	0.0350	0.1770	0.0120
Electric, radio and tv.	1.0681	0.0831	0.0740	0.0625	0.1790	0.0581
Body cars, trailers and semi-trailers.	0.5799	0.0831	0.0578	0.0543	0.1897	0.0383
Autoparts	0.2986	0.0831	0.0522	0.1039	0.1853	0.0576
Other	0.4341	0.0831	0.0508	0.0847	0.1857	0.0141

Fuente: Elaboración propia en base a ENDEI.

Some similar issues are noted in Table 7. In this case, only the attribute of scientific knowledge base does not differentiate between sectors. On the other hand, some sectors show important differences in their learning by combining different levels of attributes of sectoral schemes. For example, food ranks very well in the use of technologically based knowledge and in accumulativity, but is intermediate in appropriability and low in appropriability. On the other hand, medical instruments leads the ranking of formal and informal appropriability and opportunity, but shows low levels of informal appropriability and means in knowledge based on technology and accumulation.

From the comparison between Tables 6 and 7, some interesting observations arise because the indicator of innovative success from access to international markets is more demanding than access to new markets, then it is possible that while some learning efforts faced by the firms have effects on the possibilities of accessing new local markets, although not the case for international markets. Examples of this are the leather, food, common metals and electrical, radio and television sectors that lose between 4 and 5 positions on average. Some sectors, however, are in the best conditions in both variables of innovative success, for example, wine, machinery and equipment and agricultural and forestry machinery. There are also two cases where efforts are more profitable in foreign markets than domestic, pharmaceutical and medical instruments.

Lastly, Charts 1 to 4 compare the levels of effort expended on innovation in sales, linkages with customers and suppliers, use of protection mechanisms and persistence with the efficiency of each of these efforts measured through Opportunity, the technological knowledge base, appropriability and accumulation obtained from the model of access to external markets (Table 7). As we can see, these efforts do not always correspond to their effectiveness. For example, the Machinery and Equipment sector spends on innovation activities below the industry average, but the effectiveness of this (opportunity) spending is significantly higher than the industry average. On the other hand, in other sectors such as wine and other fermented beverages and refrigerators, both the expenditure realized and its efficiency go in the same direction, in the first case both above average and in the second, both below.

Chart 1. Oportunity vs. innovation expenditures

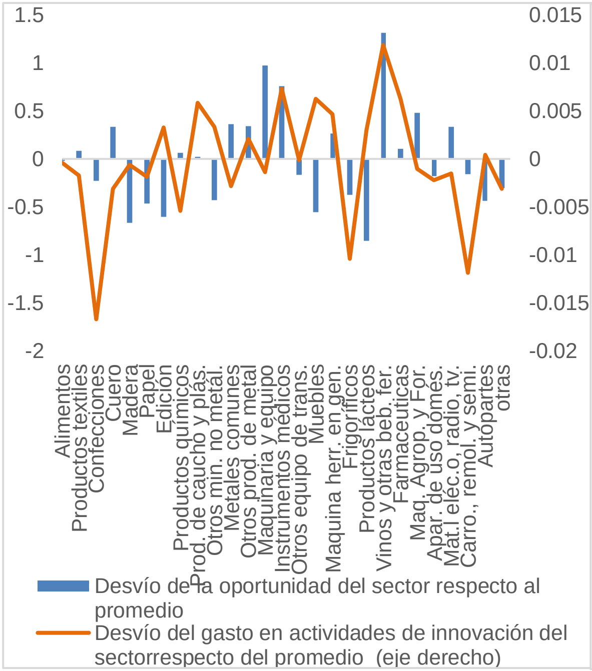


Chart 2. Knowlegde base (tech.) vs. linkages with other firms

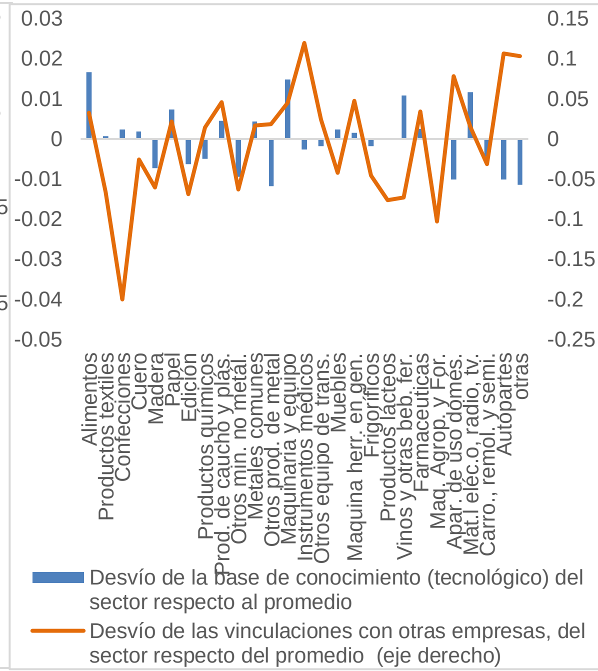


Chart 3. Appropriability vs. apropiability strategy formal e informal

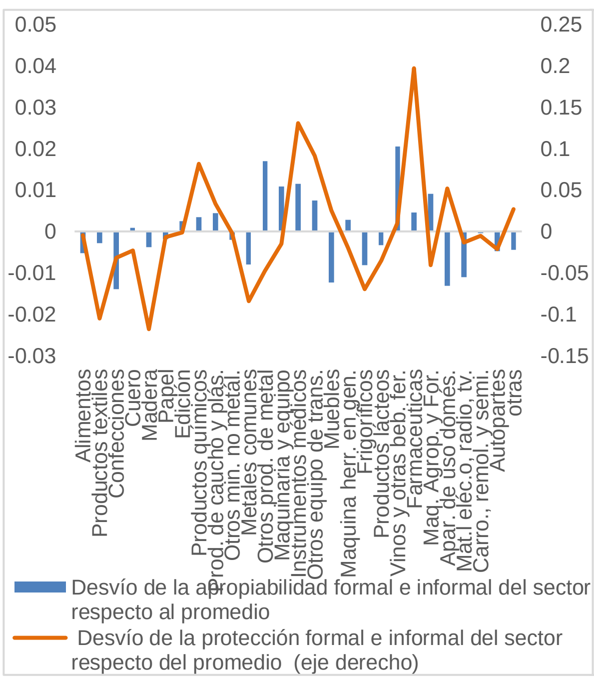
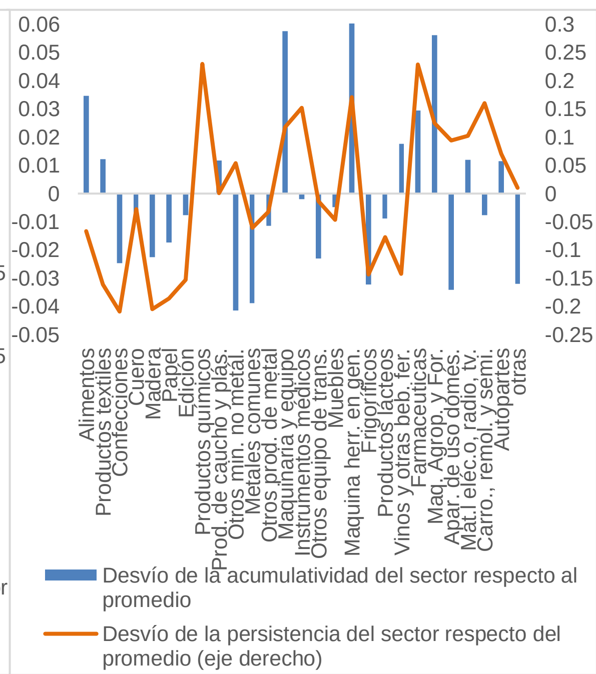


Chart 4. Cumulativeness vs. persistence



Source: own elabotarion based on ENDEI

c. Towards a sectoral taxonomy that considers the four attributes of sectoral innovation regimes

For the construction of the taxonomy we are confined to the results of the model 6 that considers as a dependent variable access to international markets since this variable is put a higher standard on the measure of innovative success. However, a similar analysis can be made with the other dependent variable with relatively similar results.

In this section, we propose a sector classification criterion that synthesizes the information presented. From the data in Table 7, we sort the branches of activity into rankings according to each of the attributes of the sectoral regimes and then compare these rankings with each other. This allows us to characterize sectors according to: (i) consistency between attributes (when the sector is in similar positions in the rankings of each attribute), and (ii) the average ranking of the different attributes that indicates the location of the sector in a continuum that goes from low to high effectiveness in the efforts made. Figure 1 summarizes this information for the model 6 estimates. The abscissa axis shows the average of the locations (at the lowest average position greater importance of the attributes, taken as a whole.) On the other hand, in the axis of the ordinates indicates the range between the ranks of each attribute for a given sector, ie the difference between the highest and lowest position it occupies (the smaller the range the greater the coherence). Given that ENDEI is representative for 27 sectors (two and four digits), both indicators can take at least 1 and at most 27[4].

In this way, we propose a characterization of the sectors according to the quadrants in which they are located. In the southwest quadrant, we find the effective and complex learning sectors. These sectors present systematically high values in the attributes of the sectorial regimes (first positions of the ranking), that means, high level and coherence. In the southeast quadrant, there are ineffective learning sectors, that consistently show low levels in the mentioned attributes (last positions of the ranking), that is to say, low level and high coherence. While in the upper quadrants are the sectors where the attributes are not consistent, which shows idiosyncratic learning processes. To the northwest we find the learning sectors effective and limited complexity, since in some of the attributes they do not perform well. To the northeast we find the sectors of learning of restricted effectiveness, since they show a good performance only in some of the attributes.

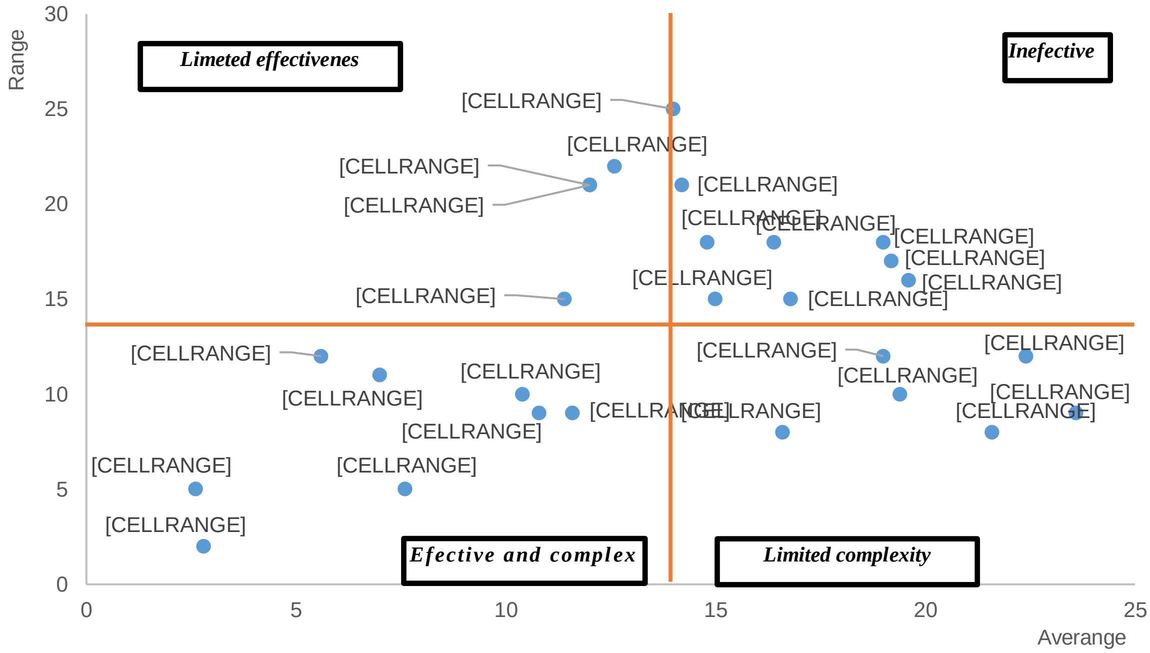
From an ordinal perspective, we can say that sectors with the greatest capacity to transform efforts into innovative success are those of effective and complex learning, followed by those of effective learning and limited complexity, those of learning of restricted effectiveness and finally those of ineffective learning. In this direction, the proposed taxonomy coincides in some sectors with what is expected according to the literature. For example, pharmaceuticals and those branches referred to machines are located in the most dynamic quadrant and other nonmetallic minerals and wood are located between the branches of minor dynamism. However, we also find other cases that, a priori would go against what was expected as textile and leather, among the most dynamic and household appliances and autoparts, among those of low and medium low dynamism. For the latter cases, if one considers the type of actor involved and its insertion in the global value chains, its low performance is understood both in effectiveness and especially in the efforts made (see Graphs 1 to 4). On the other hand, in the cases of Textile Products and Leather there is a relatively high efficiency (slightly above average) with innovation and learning efforts that are always below average. In a context of high levels of innovation success, the above results in high effectiveness.

It is convenient to clarify that this taxonomy refers to the effectiveness of the efforts and learning carried out more than the level of these, which contrasts with other criteria present in the literature in which the firms have been characterized according to the level and balance of activities (Lugones et al, 2000 and Lugones and Suárez, 2006), or to the intensity of R&D spending (Hatzichronoglou, 1997 and Bianco and Sessa, 2009). On the other hand, the taxonomy proposed by Marin and Petralia (2015) does take into

[4] For example, the Wines and other fermented beverages sector ranked first in the ranks of opportunity, informal appropriation and formal and informal appropriation, while it was fourth in terms of technological know-how and sixth in cumulative. Therefore, in the average ranking obtained 2.6, which shows a high average effectiveness, while in the range obtained is 5. This means that the sector of Wines and other fermented beverages shows high effectiveness and high consistency.

account the effectiveness, but exclusively of R&D efforts and innovation costs taken as a whole, but not other sources of learning (interactions, persistence, protection to copy).

Chart 2. Sectors by ranking and range in sectoral patterns attributes (nueext)



Fuente: Elaboración propia en base a ENDEI

4. Disussion

Next, we present a comparison between the taxonomy that arises from the proposed exercise and other sectoral taxonomies found in the literature. Given that the sectors identified as high and medium high technological dynamism by Hatzichronoglou (1997) coincide with those of specialized and science-based suppliers of Malerba and Orsenigo and those of the Schumpeter Mark II type in Malerba and Orsenigo (1997) and With the engineering intensive in the taxonomy of Katz and Stumpo (2001). And, on the other hand, Hatzichronoglou (1997) low and medium low technological sectors show a high overlap with those dominated by Pavitt's intensive suppliers and scale, Marleba and Orsenigo's Schumpeter Mark I and those based on manufacturing or natural resources of Katz and Stumpo, we present a table that compares these four classification criteria with the criterion to which we arrived in our analysis (Table 8).

On the other hand, as the taxonomy proposed by Marin and Petralia (2015) shows significant differences with the previous ones, a separate table compares this taxonomy with that arising from our exercise (Table 9).

Tabla 8 - Comparison of the proposed taxonomy with Katz and Stumpo (2001), Pavitt (P), (KS), Malerba and Orsenigo (1997) (MO) and Hatzichronoglou (1997) (OECD)[5]

		Proposed taxonomy	
		Efective and complex / limeted complexity	*Limeted effectiveness / uneffective*
Technological dynamism by KS, MO, OECD	*High*	Machinery and equipment; Machine tools; Pharmaceuticals; Agri Machines.; Other products of metal; Medical instruments; Mat.l electric, radio, tv..	Other transport eq. autoparts, household appliances, body cars and trailers
	low	Texiles, leader, rubber and plastic, wines, food, chemicals	Aparell, paper, edition, metals, furninure, wood, other non metalic prod., meat, dairy products

Source: own elaboration based on ENDEI, Hatzichronoglou (1997), Katz and Stumpo (2001), Malerba and Orsenigo (1997) and Pavitt (1984).

The sectors classified as high technological dynamism by the taxonomies of Katz and Stumpo, Pavitt, Malerba and Orsenigo and OECD coincide in the majority with the sectors classified in our taxonomy as effective and complex or effective of limited complexity. This rule is circumvented by those sectors that in Argentina are reached by special promotion schemes and which, due to the characteristics of these regimes, are encouraged to insert themselves into the global value chains in an armory stage: Autoparts, Body cars, trailers and semi-trailers, Others Transport equipment and household appliances. Regarding the sectors considered to be of low technological dynamism, most of them correspond to sectors classified in our taxonomy as being of limited effectiveness or ineffective, but there are also some that in our taxonomy are effective and complex or effective sectors of limited complexity. These are mainly sectors related to natural resources in which there exist in our country greater relative opportunities of learning linked to the pattern of productive specialization. In this sense, it should be noted that, although food production occupies a central place in our production matrix, this item is made up of very heterogeneous sectors in terms of their learning opportunities. From the level of disaggregation reached by the ENDEI, we find that sectors such as dairy products and refrigerators have very low learning opportunities while wines and other fermented beverages are the most dynamic. The case of Textile products and a certain measure Cuero also, fall within the group of high dynamism because they register low efforts of learning in the different areas, but high values of the indicator of innovative success, possibly based on a strategy of differentiation based In the design (see Charts 1 to 4).

[5] in order to compare taxonomies, we consider the sectors that Katz and Stumpo (2001) classify as intensive engineering, which Malerba and Orsenigo (1997) classify as Schumpeter Mark II and those that Hatzichronoglou (1997) classifies as high technological dynamism High and medium high technological content. We consider the other sectors to be of low technological dynamism.

Tabla 9 - Comparación de la taxonomía propuesta con Marin y Petralia (2015)

		Propose taxonomy	
		Efective and complex / limeted complexity	*Limeted effectiveness / uneffective*
Technological dynamism by Marin y Petralia (2015)	*High*	Textiles, leader, wines food,	Apparel, wood, other non metalics prod. meat, dairy products,
	Medium	machinery and equipment, tool machines, agri machines, pharmaceutical, chemicals, medical devices	Editionn; Metals
	Low	Rubber and plastics, elec. radio and tv.	Paper, other trasnport eq. furniture, autoparts, hosehod appl. body cars, and trailers

Source: own elaboration based on ENDEI and Marin and Petralia (2015)

On the other hand, the sectors classified as high technological dynamism according to the opportunity by Marin and Petralia (2015) are mostly based on natural resources and even tend to show an ordering contrary to the other taxonomies. When comparing its results with those that emerge from our analysis (Table 9) we note some coincidences: Leather, Textile products, Food, Wines and other fermented beverages, Rubber and plastic products. However, the rest of the low-dynamic or resource-based sectors fall within the restricted or ineffective groups. Thus, by including the four attributes within the analysis sectoral ordering, although it differs in some cases, in others they retain their location within the categories of high dynamism. Thus, while for Marín and Petralia (2015), machinery, electrical equipment, radio and television, chemical products, pharmaceuticals and medical instruments, are medium or low in the proposed taxonomy are among the sectors of high dynamism.

5. Conclusions

Throughout this paper, we characterize industries of Argentine manufacture according to the four attributes of technological regime. In our analysis, we consider opportunity, appropriability, knowledge base conditions and cumulativeness (Malerba and Orsenigo, 1997), to obtain a better understanding of learning processes of each industry. This perspective differs from some previous contributions that focused exclusively on opportunity. Through the estimation of multilevel models, we identify the specific contribution of industries regarding to transformation of: innovation efforts (r&d), appropriation strategies and forms of learning (based on experience or interaction with suppliers and customers or with universities and technological centres) in successful innovations. With these results, we propose a taxonomy to classify Argentine manufacturing industries according to the degree of coherence and effectiveness of their efforts.

We find that not only opportunity is relevant to explain innovative success but also appropriability, knowledge base and cumulativeness. This result indicates that learning is a complex process, therefore driving technological *upgrading* effectively require attending this multiplicity of dimensions involving technical progress instead of focusing only on expenditure on innovation activities. We also find that industries significantly differ regarding to the relevance of these attributes in the learning process, then, productive structure condition technological dynamism and technologically dynamic sectors should be defined taking into account the four attributes of technological regimes and not only opportunity.

Comparison between sectoral taxonomies considering technological dynamism (OECD, Pavitt, Katz and Stumpo, Marleba and Orsenigo), the taxonomy based on the technological opportunity of Marin and Petralia (2015) and the taxonomy suggested in this study, there are relevant differences. First, our taxonomy has similarities with both the technological dynamism one and the opportunity one. Second, some industries that are conventionally recognized as industries with low technological dynamism, are classified in our taxonomy as industries with complex and effective learning. This result is consistent with Marin and Petralia (2015). On the other hand, some industries with high opportunity, fail to reach high levels high in other dimensions, so our taxonomy is more similar to conventional taxonomies than to the taxonomy that only considers opportunity.

Results suggest opportunity is an attribute more sensitive to technological and productive environment, so industries classified as technologically dynamic from estimates based on opportunity, differ according to context considered, for example, if it is a developed or underdeveloped economy and the technological paradigm in course. Our taxonomy, which considers the four attributes of technological regimes, lies at an intermediate point between both taxonomies, may be due to that appropriability, knowledge base and cumulativeness are attributes less sensitive to changes of technological paradigm and productive environment.

Annex 1

Table 1 – Sectoral taxonomies compared

Taxonomy	Industry	Hatzichronoglou (1997) (OCDE)	Katz and Stumpo (2001)	Pavitt (1984)	Malerba and Orsenigo (1997)	Marin and Petralia (2015)
effective and complex	Textiles	low	labor intensive	supply dominated	SM1	high
	Leather	low	labor intensive	supply dominated	SM1	high
	Rubber and plastic products	middle low	natural resources intensive	production intensive	SM2 concentrated	low
	Machinery and equipment	middle high	engeneering intensive	specialized suppliers	SM2 not concentrate	medium
	Machine and tool for general purpose	middle high	engeneering intensive	specialized suppliers	SM2 not concentrate	medium
	Wines and other beverages from fermented materials.	low	natural resources intensive	supply dominated	otro	high
	Pharmaceutical	high	engeneering intensive	science based	SM2 concentrated	medium
	Agricultural and forestry machinery	middle high	engeneering intensive	specialized suppliers	SM2 not concentrate	medium
effective with limited complexity	Food	low	natural resources intensive	supply dominated	otro	high
	Chemical	middle high	natural resources intensive	production intensive	SM2 concentrated	medium
	Other metal products	middle low	engeneering intensive	supply dominated	SM1	medium
	Medical instruments	high	engeneering intensive	science based	SM2 not concentrate	medium
	Electrical equipment, radio and tv.	high	engeneering intensive	production intensive	SM2 not concentrate	low
limited effectivity	Clothing	low	labor intensive	supply dominated	SM1	high
	Paper	middle low	natural resources intensive	production intensive	SM1	low
	Edition	low	labor intensive	supply dominated	SM1	medium
	Common metals	middle low	natural resources intensive	production intensive	SM2 concentrated	medium
	Other transport equipment	middle high	engeneering intensive	production intensive	SM2 concentrated	low
	Furniture	low	labor intensive	supply dominated	SM1	low
	Auto parts	middle high	engeneering intensive	specialized suppliers	SM2 concentrated	low
ineffective	Wood	low	labor intensive	supply dominated	SM1	high
	Other non-metallic minerals	middle low	natural resources intensive	production intensive	SM1	high
	Meat	low	natural resources intensive	supply dominated	otro	high
	Dairy products	low	natural resources intensive	supply dominated	otro	high
	Household appliances	middle high	engeneering intensive	specialized suppliers	SM1	low
	Motor vehicles, trailers and semi.	middle high	engeneering intensive	production intensive	SM2 concentrated	low

Source: Own elaboration base don ENDEI, Hatzichronoglou (1997), Katz and Stumpo (2001), Malerba and Orsenigo (1997), Marin and Petralia (2015) and Pavitt (1984)

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