www.cya.unam.mx/index.php/cya

Contaduría y Administración

Accounting & Management

Contaduría y Administración 69 (4), 2024, e470

Determining factors of innovation in the manufacturing sector of the province of Córdoba, Argentina

Factores determinantes de la innovación en el sector manufacturero de la provincia de Córdoba, Argentina

Verónica Arias, Norma Patricia Caro*

Universidad Nacional de Córdoba, Argentina

Received September 05, 2022; accepted October 31, 2022
Available online February 25, 2025

Abstract

Innovation in products or processes is a topic of interest for industries in the province of Córdoba, Argentina, so with the aim of evaluating the determinants of innovation.
Innovation, the probability of obtaining innovative results was modelled through a set of factors characteristic of firms and their environment, using a mixed logistic model.
The results indicate that factors such as the size of the firm, the percentage of sales dedicated to investment in innovation activities, the continuity of the innovation effort, the use of funds from public development programmes, among others, influence the probability of achieving product or process innovation.

JEL Code: O31, C25
Keywords: innovation; mixed logistics model; Argentinean industries

*Corresponding author.
E-mail address: pacaro@unc.edu.ar (N. P. Caro).
Peer Review under the responsibility of Universidad Nacional Autónoma de México.

http://dx.doi.org/10.22201/fca.24488410e.2024.4796

Resumen

La innovación en productos o procesos es un tema de interés para las industrias en la provincia de Córdoba, Argentina, por lo que, con el objetivo de evaluar los factores determinantes de la misma, se modeló la probabilidad de obtener resultados innovadores mediante la consideración de un conjunto de factores característicos de las empresas y de su entorno aplicando un modelo logístico mixto.
Surge de los resultados que factores como el tamaño de la firma, el porcentaje de las ventas destinados a inversión en actividades de innovación, la continuidad en el esfuerzo innovador, la utilización de fondos de programas públicos de fomento, entre otras, influyen sobre la probabilidad de lograr innovaciones en producto o procesos.

Código JEL: O31, C25
Palabras clave: innovación; modelo logístico mixto; industrias argentinas

Introduction

Innovation is a complex process through which companies transform knowledge into added value. There are various definitions of innovation. According to the Oslo Manual (OECD, 2005), innovation is understood as the introduction of a new or significantly improved product (good or service), a process, a new marketing method, or a new organizational method in the company's internal practices, the organization of the workplace, or the relations external to the company. In this research, the analysis is focused on the different factors associated with achieving innovative results in products or processes in industrial firms in the province of Cordoba, Argentina.

There is great interest in understanding the variables that affect the innovation process, as it is widely recognized as one of the key factors of competitiveness and long-run economic growth. Innovation is crucial in accessing markets for more differentiated, dynamic, and higher-priced products. In this regard, Arza et al. (2017) find empirical evidence favoring this hypothesis in the Argentine case. Firms that base their competitiveness on the search for and incorporation of new technologies can see their impact in reducing costs, enabling greater competition via prices, or positioning themselves in niches or segments of higher value with the consequent improvement in profitability. Thus, firms are better positioned to make new expenditures on R&D and other innovation activities, increasing their chances of obtaining innovations and restarting the cycle (Barletta et al., 2013).

This research aims to identify characteristics and actions at the company level that impact the probability of obtaining innovative results. This can lead to designing and adapting the companies' decisions and public sector measures to promote them.

This paper seeks to contribute to understanding the innovation process in industrial manufacturing companies in the province of Córdoba. Located in the central region of Argentina, it has a

http://dx.doi.org/10.22201/fca.24488410e.2024.4796

population of 3 978 984 inhabitants (INDEC , provisional results CNPHyV 2022) , and is the second most populated province. In the period under analysis, its economy represents, on average, 8.9% of the national value added at constant 2004 prices. Its main economic activities are agriculture, livestock, and industry. The food, automotive, and machinery and equipment industries are the most important within the latter. The average share of the manufacturing industry in the provincial gross product, at constant 2004 values, was 19%.

For the preceding reasons, studying innovation in the sector's companies is very important. The data came from the Technological Innovation Survey (EIT; Spanish: Encuesta de Innovación Tecnológica), carried out by the General Directorate of Statistics and Censuses of the Province of Cordoba. The observations and measurements submitted by each company over time (longitudinal data) for 2011-2016 are used. A logistic mixed model is applied to evaluate and identify the main variables linked to the analyzed firms that help explain the probability of firms being innovative in products or processes.

The article has the following structure: an introduction in which some background information and the main objective of the work are presented, then the theoretical framework with the main contributions to the subject that have been taken into account. Next, the methodology is described: variables, sample, and method used, then the results obtained, and finally, the conclusions.

Theoretical framework

As Heijs and Buesa (2016) point out, innovation is no longer considered a process involving a small number of people but a process that must necessarily include the contribution of various actors and in which interactions and its external environment are of essential importance.

While there is consensus on the recognition of innovation and technological change as a crucial source of economic development, the many aspects of this phenomenon have meant that the determinants of innovation are still a subject of study. There is an extensive literature on innovation that highlights various aspects of this process. The conceptual framework for developing empirical studies comes from Schumpeter's (1939) critique of neoclassical economics and his definition of innovation as a driving force for economic development, evolutionary ideas, and the systemic view of innovation.

The many aspects involved in the innovation process and its significant complexity mean that its study can be approached from different perspectives. This paper concentrates on the factors that influence the probability of manufacturing companies in the province of Cordoba obtaining innovative results in products or processes.

Among the determinants of company-level innovation, beyond the objectives pursued in the various studies, the literature emphasizes companies' structural characteristics, innovation behavior, and environment (Milesi et al., 2011).

One widely analyzed factor is the size of the companies. Accordingly, some studies support the well-known "Schumpeterian hypothesis," which considers large companies with market power to have the greatest innovation possibilities (Crespi & Zúñiga, 2012). Arias Ortiz et al. (2013) mention other research that refutes these conclusions, considering that small companies are more flexible, have greater adaptability, and have less complex organizational structures, which favors innovation and the development of new projects.

In several studies for Argentina, this variable alternates its sign. Research such as Chudnovsky et al. (2006) and Crespi and Zúñiga (2012) find that larger companies are more innovative. Meanwhile, works such as those of Bachmann (2016), Marín et al. (2017), Astudillo Durán (2018), and Gómez and Borrastero (2018) refute these conclusions, finding a negative or non-meaningful relation between size and the achievement of innovative results.

Other variables commonly included in studies on the determinants of innovation are those related to the efforts made by companies (innovative input), both in research and development (R&D) and in other innovation activities, such as the acquisition of machinery and equipment, hardware, software, technology procurement, and consulting. The technology the company uses today depends on the technology used in the past. A central role in the innovative process is played by learning, where companies are not only nourished by the accumulation of experience but also by external sources such as consumers, universities, consultants, research centers, and competitors (Lundvall, 1992). In this context, innovation is a process of knowledge accumulation through its activities and interaction with the environment in which the agents operate.

Another important factor is companies' absorptive capacity, i.e., the ability to recognize the value of new information, assimilate it, and apply it for commercial purposes. This capacity is a function of prior technological knowledge, investment in research and development, learning in the manufacturing and design process, and human resource training (Cohen & Levinthal, 1989).

Mairesse and Mohnen (2010) confirm the existence of a positive relation between research and development (R&D) expenditure and the achievement of innovative results, especially if they are carried out continuously. An example of this is the study by Griffith et al. (2006) for France, Germany, Spain, and the United Kingdom. Equivalent results are found for developing economies. There is evidence that higher R&D expenditures lead to a higher propensity to introduce technological innovations in companies in Chile (Benavente Hormazábal, 2005), Brazil and Mexico (Raffo et al., 2008), Argentina (Chudnovsky et al., 2006; Raffo et al., 2008, Arza & López, 2010).

Crespi and Zúñiga (2012) point out that companies' innovation activities in many Latin American economies are based on imitation and technology transfer, acquisition of machinery and equipment, and purchase of disincorporated technology. In their study they incorporate both intra-mural innovation activities (internal R&D and engineering and design) and the remaining innovation activities, finding a positive effect of all activities on the achievement of innovative results for all the countries analyzed. The same result is obtained by the research for Argentina by Marin et al. (2017) and Gómez and Borrastero (2018).

Investment in innovation activities requires a great effort from companies. From the review of studies conducted by Mairesse and Monhen (2010), it appears that most of them conclude that public financing of research and development leads to greater investment in innovation activities and greater innovative results and does not displace private spending by the public.

In Latin American countries, government support for financing R&D is essential. Crespi and Zúñiga (2012) state that the high costs and risks of innovation and the difficulty for companies to wait long periods to see results are the main obstacles to innovation, as perceived by companies in the region. In their research, they conclude that there is a positive relation between public financing and spending on innovation activities in the cases of Chile, Colombia, and Costa Rica. However, the relation is not significant in the case of Argentina. On the other hand, Petelski et al. (2017), in their study of public financing for innovation in Argentina, found evidence of a positive impact on the intensity of the R&D efforts of industrial companies.

Companies often carry out innovation activities in collaboration with customers, suppliers, universities, laboratories, etcetera. Cooperation allows the sharing of knowledge, benefitting from complementarities, reducing risks, and saving costs. Starting from evolutionary ideas in the early 1990s, the innovative process was approached from a systemic perspective (Freeman, 1987; Lundvall, 1992; Nelson and Rosenberg, 1993; Edquist, 1997, among others). In the innovation systems approach, interrelations and cooperation networks are the fundamental elements in the innovation and production process. The innovation system has been called the set of agents, institutions, and regulations that support the processes of technology incorporation, which determines the generation, adaptation, acquisition, and diffusion rate of technological knowledge in all productive activities (Nelson & Rosenberg, 1993).

Mairesse and Monhen (2010) find in their review of works for industrialized countries that cooperation in innovation activities (R&D or design) is associated with higher levels of investment in these activities. Raffo et al. (2008) reach the same conclusion for a group of European countries when cooperation is international. For Latin American countries, however, their findings are different. Crespi and Zúñiga (2012) find partial evidence for a group of Latin American countries. The relation is significant in the case of Colombia, Panama, and Uruguay but not for Argentina, Chile, and Costa Rica. This result may show a weak development of innovation networks in these countries.

Other variables included in most empirical studies reviewed are the company's age, the capital's origin, its international status, the training of human resources, and the industrial sector to which it belongs.

Based on the above, it can be concluded that the empirical evidence on the determinants of innovation is extensive and does not show conclusive results. The innovation process is a complex phenomenon in which dynamic relations prevail and the innovation-related factors vary and change.

In Latin America, studies have been conducted to determine which innovation factors are relevant in a changing context in which adaptation is necessary as a key to competitiveness. Among these studies are Sarmiento Paredes et al. (2018) on the textile sector in Mexico, Acuna-Opazo and Castillo-Vergara (2018) on the manufacturing industry in Chile, and Lopez and Gomez (2022) on companies in Colombia.

Methodology

Sample and variables

The data used come from the Survey of Innovation and Technological Behavior, carried out from 2011 to 2016 by the General Directorate of Statistics and Census of the province of Córdoba. It is provincially representative of the industrial sector.

The total number of available companies was separated into two samples: one to model fit, composed of those for which complete information was available for the last five years analyzed (training sample), and the other to validate the model on new data (validation sample), in which all the remaining companies were included (Table 1). Both groups included those companies that had, on average, between 5 and 250 employees (SMEs) during the period analyzed.

The data used are the observations and measurements submitted by each company over time, constituting longitudinal or panel data. Information from all available years was considered in the training sample, and in the second group, the values from the last year in which the company responded to the survey were used.

Table 1
Companies and observations in the sample

Sample	Number of companies	Number of observations
Training	276	1.631
Validation	232	232
Total	508	

Source: created by the authors

A logistic mixed model is fitted to evaluate the main variables considered relevant in the theoretical framework. The response variable considers whether the company achieved new or significant improvements in new products or processes for the national or international market. This variable is binary and indicates whether the company innovated or not (innovates=1 / does not innovate=0). The predictor variables are indicators linked to the characteristics and behavior of the firms and their relation with the national innovation system. Table 2 below shows the variables considered in the model with their respective conceptual definitions.

Table 2
Variables included in the model

Variable	Name	Description
Dependent variable:		
Innovation	INNOVA	1, if the company achieved new products or processes or with significant improvements, novelties for the national or international market 0, otherwise
Predictive variables:		
Size	LN_RRHH	Size of the company, measured by employed personnel (in logarithm)
Efforts in innovation activities	AI_ENDO_VTA	Percentage of spending on endogenous innovation activities (internal research and development, training, and industrial design and engineering) relative to total sales
	AI_EXO_VTA	Percentage of spending on exogenous innovation activities (external research and development, acquisition of machinery and equipment, hardware, software, technology procurement, consulting) relative to total sales
	AI_ENDO_CONT4	1, if the company spent on in-house R&D, training, or industrial design and engineering activities continuously for 4 years or more 0, otherwise.
Relation to the National Innovation System	FONDOS_PROGOFIC	1, if the company used funds from official innovation promotion programs to finance its activities. 0, otherwise
	VINCULA	1, if the company carried out any activity related to public or private bodies of the national innovation system

	(Universities, INTI, INTA, CONICET, other governmental agencies, customers, suppliers, laboratories, etcetera.) 0, otherwise

Source: created by the authors

Regarding the dependent variable, the company defines success in the innovation process. The questionnaire asks the firm to state whether the innovation activities have led to innovative achievements in the reference year. Innovations are identified by disaggregating the object they innovated (product, processes, organization, marketing) and whether it was new for the company or the national or international market.

New or improved product innovation is defined as: "the introduction to the market of a technologically new product (whose technical specifications, components, materials or functional characteristics differ significantly from those of the company's previous products) or a significantly improved product (a previously existing product whose performance has been improved or greatly enhanced)." On the other hand, innovation in new or improved processes involves recreating or modifying the process of manufacturing products or providing services as a result of using new equipment, inputs, or technological solutions, or introducing changes in the organization of the production process. It includes modifications in the logistics of inputs or finished products (OECD, 2005).

The companies that constitute the sample with which the model was adjusted show similar characteristics to those in the validation sample. As shown in Table 3, on average, in 2011-2016, 27% of the companies in the training sample achieved, due to their innovative efforts, new products or processes, or significant improvements that were new for the national or international market. The validation sample is composed of 29% of innovative companies.

Table 3
Ratio of innovative companies, average 2011-2016

		Muestra	
		Training	Validation
INNOVA	YES	27%	29%
	NO	73%	71%

Source: created by the authors

As already indicated in Table 2, one of the variables evaluated in the model is company size, which, following the recommendations of the Oslo manual (2005), is measured by the number of employees. In both samples (training and validation), innovative companies are, on average, larger than

http://dx.doi.org/10.22201/fca.24488410e.2024.4796

non-innovative companies. Half of the innovative companies in the training sample have up to 38 employees, while the non-innovative companies have 19 employees or less.

Among the predictor variables related to the innovation efforts made by the companies, the expenditure ratio on innovation activities related to sales is included in the model. Activities endogenous to the company are analyzed separately, such as expenditure on internal research and development, expenditure on training or industrial design and engineering, and innovation activities exogenous to the company, which include spending on external research and development, acquisition of machinery and equipment, hardware, software, technology procurement, or consultancy. In the companies that make up both samples, investment in machinery and equipment is the main activity (74%), followed by internal research and development (9%) and industrial design and engineering (8.5%). Innovative companies spent an average of 1.2% of their sales on endogenous innovation activities, while non-innovative companies invested an average of 0.1%. Meanwhile, 3.7% of sales were allocated to exogenous innovation activities in companies that achieved innovative results. In comparison, companies that did not innovate in products or processes spent an average of 1.2% of sales on these activities (Table 4).

Table 4
IA expenditures as a % of total sales, average of the period 2011-2016

	Training Sample		Validation Sample	
	INNOVATE		INNOVATE	
	YES	NO	YES	NO
IA_Endogenous / Sales	1.2%	0.1%	1.2%	0.1%
IA_Exogenous / Sales	3.7%	1.2%	4.2%	0.8%

Source: created by the authors

Some of the obstacles pointed out by the companies to investing in internal R&D are its high risks and costs, as well as the need for access to credit. Regarding using resources from official programs to promote innovation, 22% of innovative companies have used them. Of the non-innovative companies, 6% used this source of financing.

Companies do not innovate in isolation. The innovation process involves a system of interactions and interdependencies between companies and other organizations and institutions. 48% of the innovating companies (training sample) declared having had some type of link with public or private entities of the national innovation system (Universities, INTI, INTA, CONICET, other government agencies, clients, suppliers, and laboratories, among others)[1], either cooperative agreements with active

[1] INTI: Instituto Nacional de Tecnología industrial (National Institute of Industrial Technology); INTA: Instituto Nacional de Tecnología Agropecuaria (National Institute of Agricultural Technology); CONICET: Consejo Nacional de Investigaciones Científicas y Técnicas (National Council for Scientific and Technical Research)

http://dx.doi.org/10.22201/fca.24488410e.2024.4796

participation or formal or informal exchange of information. Among the companies that did not achieve innovative results, 13% maintained some link with these institutions.

Method

One of the assumptions of the logistic regression model is that the observations of the response variable are independent of each other, but there are many situations in which the data present a cluster or multilevel structure. An example is when information is collected from individuals or units of analysis at different points (repeated measures/longitudinal data) or when individuals are nested in larger units, families, groups, or classes. Whatever its origin, this grouping causes observations to be correlated within groups since the units share the same environment or have similar characteristics. The independence assumption is not met, and ignoring this relation and omitting the importance of intra-group dependence can lead to incorrect inferences (Rabe-Hesketh & Skrondal, 2012). Consequently, generalized linear mixed models should be used.

Generalized linear mixed models (GLMM) make it possible to model situations where the response variable has a non-normal distribution, incorporating random effects for the units/groups. In these models, as the units at each level are considered random samples of a population, they contribute to the model by incorporating random effects. The latter allows for random regression coefficients that reflect intra-unit variability through the variability of the intercepts or slopes.

Let y_i be the vector of responses of subject i, where y_{ij} is the response at time j of subject i, such that i = 1,...,q, and j = 1,...,t_i. It is assumed that, conditional on the random effects α_i, the elements y_{ij} are independent. All y_{ij} have density function of the form:

$$f_{ij}\left(y_{ij} \mid \alpha_i, \theta_{ij}, \phi\right) = \exp\left\{\left[y_{ij}\ \theta_{ij} - b(\ \theta_{ij})\right] / a(\phi) + c(y_{ij}; \phi)\right\}$$

The conditional mean $E(y_{ij} \mid \alpha_i) = \mu_{ij}$ is modeled through the linear predictor η_{ij}, which is formed as a combination of fixed and random effects,

$$\eta_{ij} = x'_{ij}\beta + z'_{ij}\alpha_i \tag{3.5}$$

and a known link function $g(\mu_{ij})$ that relates the conditional mean to the linear predictor. The vectors x_{ij} and z_{ij} contain the known values of the covariates, associated with β (p x 1) vector of fixed effects and with α_i (k x 1) vector of random effects of cluster i, respectively. Additionally, α_i is assumed

http://dx.doi.org/10.22201/fca.24488410e.2024.4796

to be multivariate normal distributed with mean 0 and covariance matrix Σ, and its density is denoted as $f(\alpha_i \mid \Sigma)$.

The model can be fitted by maximizing the marginal likelihood. In mixed effects models, the linear predictor is composed of a combination of fixed and random effects. Fixed effects are those variables for which the researcher has only included the interest levels. In the case of a fixed effect, the interest is in comparing the dependent variable's results for different explanatory variable levels.

On the other hand, a quantity is considered random when it changes over the population units. When a variable is included as a random effect in the model, it is assumed that one seeks to draw conclusions from the population from which the observed units have been chosen and is not interested in those particular units. One unit in the sample could be exchanged for another in the population, which would be indifferent. In the case of random effects, the interest is not in the difference in means but in how the random effect explains the variability of the dependent variable.

Random effects can be incorporated as random ordinates or coefficients (slopes). The random ordinates represent the unobserved heterogeneity in the response variable as a whole, while the random coefficients represent the unobserved heterogeneity in the effects of the explanatory variables on the response variable.

To summarize, generalized linear mixed models require a correct definition of the linear predictor, including relevant interactions; an appropriate link function; correct specification of covariates that will have random coefficients; conditional independence of responses given random effects and covariates; independence between random effects and covariates; and random effects with normal distribution (Rabe-Hesketh & Skrondal, 2012).

Since the response variable analyzed in this work is binary (1. Innovates, 0. Does not innovate) and the data present a grouping structure since they are repeated measurements over time for each company, the particular model applied is a mixed logistic model with random order of origin.

The random order can be considered the combination of the effects of the set of omitted subject-specific covariates that mean some companies are more likely to innovate than others (Rabe-Hesketh & Skrondal, 2012).

The regression coefficients represent the conditional effects of the covariates, given the values of the random (subject-specific) effects.

Likelihood ratio (LR) tests and the Wald test can be used to perform inference on the model parameters.

Because the data structure shows dependence on multiple responses for each company, incorporating random effects in the regression allows unobserved heterogeneity to be modeled at the unit (company) level.

The model adjusted to identify and evaluate the main determinants of innovation is a mixed logistic model with random ordinate (the company). The response variable is binary and indicates the group to which the firm belongs (innovates=1 / does not innovate=0), and the predictor variables are indicators related to the structure of the companies, their behavior in relation to innovative efforts, and their links with other states of the national innovation system (Table 2). The model to be estimated is expressed as follows:

$$\mathrm{logit}\left\{P\left(y_{ij}=1\middle|x_{ij},\alpha_i\right)\right\}=\beta_0+\beta_1\,LN_{RRHH}+\beta_2\,AI_{ENDO_{VTA}}+\beta_3\,AI_{EXO_{VTA}}+$$
$$+\beta_4\,AI\_ENDO\_CONT4+\beta_5 FONDOS\_PROGOFIC$$
$$+\beta_6 VINCULA+b_j \tag{1}$$

Where:

$P\left(y_{ij}=1\middle|x_{ij},\alpha_i\right)=\pi_{ij}$: probability of success in obtaining innovative results in new or considerably improved products or processes, a novelty for the national or international market.

b_j: random order (company)

The glmer function available in the lme4 library of the R software was used for model fitting. The Gauss-Hermite adaptive quadrature method approximates the integral over the random effect of the likelihood function.

In order to analyze the model's predictive capacity, the observed binary classification is compared with the classification estimated by the model, and measures of sensitivity and specificity are calculated. Sensitivity measures the ratio of innovative companies (innova=1) that the model effectively classified as such, while specificity measures the ratio of companies correctly identified as non-innovative. Models with high values for both measures are desirable.

Results

From the application of the model, Table 5 shows the estimated coefficients. The sign of the coefficients is as expected for all the variables analyzed. As a random effect, the company was considered, which in some periods has innovated and others has not. The probability value associated with the likelihood ratio (LR) test shows a significant change in the log-likelihood function when going from a restricted model (without random effects) to the specified model. That is, there is a company effect explaining the higher ratio of the heterogeneity induced by the data, which justifies its inclusion as a random order.

Table 5
Estimation of the parameters of the mixed logistic model

Fixed Effects	Coefficient	Standard Error	p-value	Exp (β)
LN_RRHH	0.478	0.118	< 0.001	1.613
AI_ENDO_VTA	0.714	0.125	< 0.001	2.042
AI_EXO_VTA	0.060	0.018	< 0.001	1.062
AI_ENDO_CONT4	2.011	0.394	< 0.001	7.469
FONDOS_PROGOFIC	0.672	0.310	0.030	1.958
VINCULA	1.118	0.230	< 0.001	3.060
Constant	-4.393	0.458	< 0.001	
Random Effect	Variance	Standard Error	LR test vs. logistic regression Pr(Chibar2)	
COMPANY	2.884	1.698	0.000	

Source: created by the authors

The company's size, measured by the number of personnel employed (in logarithm), was a significant factor positively related to the company's probability of innovating in products or processes. With a unit increase in firm size measured in logarithm, the probability of innovating is 1.613 times greater than that of not innovating. This result is supported by what has been observed in other studies carried out for Argentina (Chudnovsky et al., 2006; Crespi & Zúñiga, 2012; Milesi et al., 2011) and is in line with the Schumpeterian hypothesis, according to which innovative possibilities are greater in the case of large companies with market power.

The variables in the model related to the efforts in innovation activities made by the companies, both endogenous and exogenous, were statistically significant. Those companies that invest a higher ratio of their sales in innovation activities have a higher probability of obtaining new products or processes for the market, with a greater impact of innovation activities internal to the company. Evidence of this positive relation between expenditure on innovation activities and innovative results can be found in both developed (Griffith et al., 2006; Mairesse & Mohnen, 2010) and developing countries (Chudnovsky et al., 2006; Benavente Hormazábal, 2005; Raffo et al., 2008; Arza & López, 2010; Marín et al., 2017 and Gómez & Borrastero, 2018).

Faced with a unit increase in investment in endogenous innovation activities (internal R&D, design and engineering, training) related to sales, the probability of innovating is 2.042 times greater than that of not innovating. Meanwhile, if the unit increase occurs in exogenous activities (acquisition of machinery and equipment, hardware, software, consulting, technology procurement, external R&D) concerning sales, the probability of innovating is 1.062 times greater than that of not innovating.

Chudnovsky et al. (2006) and Marín et al. (2017) emphasize in their work the importance of firms learning when innovating and that such a learning process must be continuous to be effective. The model's estimated coefficient is significant and positive regarding the continuity of endogenous IA expenditure. The probability of achieving innovations in new products or processes for the market is more than seven times higher in a company that spends on internal innovation activities continuously compared to those that do so sporadically. Thus, continuity in endogenous IA expenditure stands out as the variable with the greatest influence on the probability of obtaining innovative results. Companies that spend systematically on R&D are the ones that take the most advantage of the cumulative and learning effects derived from the continuity of technological research (Buesa et al., 2002).

The characteristics of investment in innovation imply great efforts on the part of companies to carry them out. As Crespi and Zúñiga (2012) state, one of the main difficulties perceived by firms is waiting long periods to see the results of the investment and the high costs and risks associated with innovation activities. In the model, the relation between the use of public program funds and the achievement of innovative results is statistically significant. Those firms that have used funds from official programs to promote innovation are 1.958 times more likely to obtain innovative results than those that have not.

Finally, the model evaluates the relevance of the linkage activities between the companies analyzed and the set of public or private entities in the environment where the firms carry out their productive activities. The linkage activities considered include cooperative agreements with active participation, other links, and informal exchange of information. It emerges from the model that there is a positive and significant relation between linkages and the probability of innovating. This coincides with the systemic perspective, according to which the interaction between companies and various institutions are fundamental factors in the success of the innovative process of companies (Albornoz et al., 2005). The probability of successfully innovating products or processes is three times higher in those companies that participated in linkage activities with other companies or institutions compared to companies that carried out their innovation activities individually.

In order to analyze the model's predictive capacity, the observed binary classification is compared with the classification estimated by the model, and measures of sensitivity and specificity are calculated.

Figure 1 presents the ROC curve corresponding to the fitted model, which shows all the pairs of sensitivity and complement of specificity for different cut-off points. The area under the curve (AUC) is 0.95, which shows a good ability of the model to discriminate between innovating and non-innovating companies at any cut-off point.

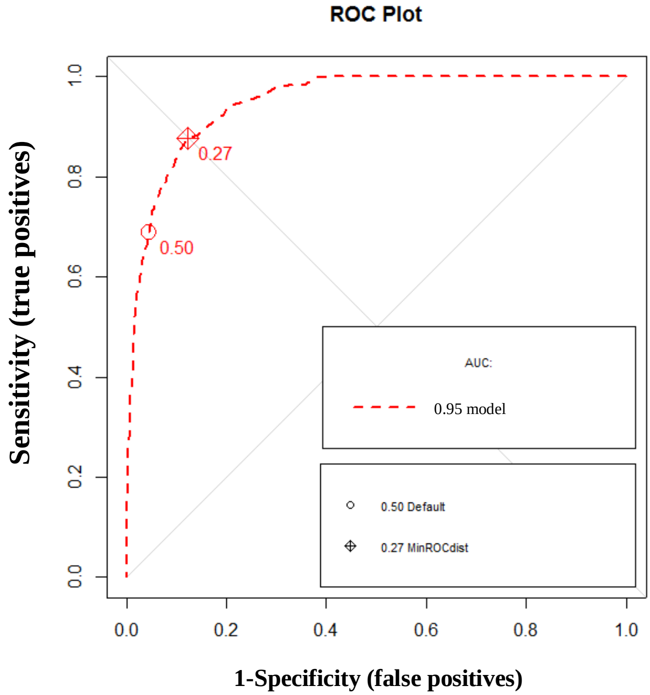

Figure 1. ROC curve

Table 6 shows the measures of sensitivity, specificity and precision for a cut-off point of 0.27, which was defined as that which minimizes the distance between the ROC curve and the point (0.1). For the training sample, the model correctly predicts 87.70% of companies that did not achieve innovations in products or processes and 87.61% of the cases of innovative companies. For the validation sample, these indicators assume values of 93.33% and 38.24%, respectively. In both groups of companies, the level of precision obtained was higher than 77%.

Table 6
Predictive capability of the model

	Training sample	Validation sample
Specificity	87.70%	93.33%
Sensitivity	87.61%	38.24%
Accuracy	87.68%	77.25%

Source: created by the authors

http://dx.doi.org/10.22201/fca.24488410e.2024.4796

According to the values of the area under the ROC curve and the classification measures shown in Table 6, good measures of the performance of the mixed logistic model as a predictive tool were obtained both for the companies in the training base and for the companies that were not part of the model fit (validation sample).

Discussion

The fitted random order logistic model results correspond to the main arguments presented in the literature review.

First, it was found that the larger the company's size, the more likely it is to innovate. Larger companies are better positioned to achieve innovative outcomes in products or processes.

Secondly, the variables referring to the companies' efforts in innovation activities positively impact the probability of innovating, especially those carried out within the firm (internal R&D, design and engineering, training). In addition, the probability of success in the innovation process is higher in companies that adopt a strategy based on continuity of investment.

Finally, funds from official innovation promotion programs and linkage activities with public or private entities, whether cooperative agreements with active participation or other links and informal information exchange, are relevant variables positively linked to the probability of obtaining innovative results.

The main limitation of this work is that the modeled variable, achievement of innovative results in new products or processes for the domestic or international market, is defined by the company itself. Therefore, it is a subjective indicator that depends on the company's perception and parameters regarding what constitutes innovation, which incorporates measurement errors of the modeled variable.

An alternative measure of innovation used in works referring mainly to developed countries is the number of patents. In the case of Latin American countries, and the case of Argentina in particular, it is not possible to use this indicator given the scarce use of this mechanism for the formal protection of innovations, thus losing representativeness.

Conclusions

Because small companies are at a disadvantage compared to larger firms, policy formulation must be oriented toward small and medium-sized enterprises (SMEs) so that they have better tools to face the obstacles and challenges present in the innovation process.

It was shown that companies that make greater efforts in innovation activities will likely obtain successful results, underscoring the need to apply policies to encourage investment in these activities. Traditional policies such as public financing for R&D, financial and tax incentives, and regulation of industrial and intellectual property rights help to achieve this objective.

Given the importance of the innovative success of continued investment in internal innovation activities, public policies should ensure that these activities are not just sporadic projects but incorporated as part of companies' routine and long-run strategy.

The model highlights the importance of not approaching innovation actions in isolation. The recommendation arises from this to reinforce policies to support institutional coordination and to encourage the generation and strengthening of networks. It is essential to have an institutional environment that manages to coordinate the actions of companies, scientific institutions, and the State, and, as Gutiérrez Rojas and Baumert (2018) propose, to work on the coordination of the system in order to transform scientific advances and technological developments into marketable products.

In order to achieve greater development of innovation activities, it is essential to foster the entrepreneurial spirit, strengthen the internal capabilities of companies to innovate and generate institutional and market conditions that allow technological improvements to prosper.

References

Acuna-Opazo, C., y Castillo-Vergara, M. (2018). Barreras a la innovación no-tecnológica: efectos sobre el desempeño empresarial en una economía emergente. Contaduría y administración, 63(3), 00. https://doi.org/10.22201/fca.24488410e.2018.1383

Albornoz, M., Estébanez, M. E., y Alfaraz, C. (2005). Alcances y limitaciones de la noción de impacto social de la ciencia y la tecnología. Revista iberoamericana de ciencia tecnología y sociedad, 2(4), 73-95. Disponible en: https://www.redalyc.org/pdf/924/92420405.pdf. Consultado: 0/03/2022.

Arias Ortiz, E.; Crespi, G.; Tacsir, E.; Vargas, F. y Zúñiga, P. (2013). Innovación para el desempeño económico: el caso de las empresas en América Latina y el Caribe. Banco Interamericano de Desarrollo, Nota Técnica 494. Disponible https://webimages.iadb.org/publications/spanish/document/Innovaci%C3%B3nparaeldesempe%C3%B1o-econ%C3%B3mico-El-caso-de-las-empresas-en-Am%C3%A9ricaLatina-y-el-Caribe.pdf. Consultado; 05/03/2022.

Arza, V., Español, P. y Herrera Bartis, G. (2017). Innovación y exportaciones en la Argentina. Un análisis del comportamiento de las empresas industriales en el marco de un cambio de régimen macroeconómico. Revista de Economía Política de Buenos Aires. (16), 9-47. Disponible en: https://ojs.econ.uba.ar/index.php/REPBA/article/view/1322. Consultado: 10/3/2022.

Arza, V., López A. (2010). Innovation and Productivity in the Argentine Manufacturing Sector. IDB Working Paper Series No. IDB-WP-187. Disponible https://publications.iadb.org/en/publication/innovation-and-productivity-argentinemanufacturing-sector. Consultado: 8/3/2022.

Astudillo Durán, S. (2018). La innovación en las mipymes manufactureras: estudio comparativo entre el Ecuador y la Argentina. Tesis de posgrado. Universidad Nacional del Sur. Bahía Blanca. Argentina. Disponible en: https://repositoriodigital.uns.edu.ar/bitstream/handle/123456789/4129/Tesis%20Doctoral%20S.%20Astudillo%20%20febrero%202018%20.pdf?sequence=1&isAllowed=y. Consultado: 8/3/2022.

Bachmann, F. (2016). Los determinantes de la innovación: un aporte para la industria argentina. Tesis de grado. Universidad Nacional de Mar del Plata. Facultad de Cs. Económicas y Sociales. Disponible: https://nulan.mdp.edu.ar/id/eprint/2474/1/bachmann.2016.pdf. Consultado: 10/3/2022.

Barletta, F.; Pereira. M.; Robert, V.; Suarez, D. y Yoguel G. (2013). Innovación y desempeño económico a nivel de firma. Una perspectiva evolucionista. Trabajo N°4 del Centro Interdisciplinario de Estudios en Ciencia, Tecnología e Innovación (CIECTI). Disponible en: file:///C:/Users/general/Downloads/Cap09-Barleta-Pereira%20(2).pdf. Consultado: 15/3/2022,

Benavente Hormazábal, J. M. (2005). Investigación y desarrollo, innovación y productividad: un análisis econométrico a nivel de la firma. Estudios de Economía, 32(1), junio, 39-67. Disponible en https://estudiosdeeconomia.uchile.cl/index.php/EDE/article/view/40871. Consultado: 8/3/2022.

Buesa, M.; Baumert, T.; Heijs, J. y Martínez, M. (2002). Los factores determinantes de la innovación: un análisis econométrico sobre las regiones españolas. Economía industrial, (347), 67-84. Disponible en https://www.mincotur.gob.es/Publicaciones/Publicacionesperiodicas/EconomiaIndustrial/RevistaEconomiaIndustrial/347/67-84%20347%20MIKEL%20BUESA.pdf. Consultado: 15/3/2022

Chudnovsky, D., López, A., y Pupato, G. (2006). Innovation and productivity in developing countries: A study of Argentine manufacturing firms' behavior (1992–2001). Research policy, 35(2), 266288. https://doi.org/10.1016/j.respol.2005.10.002

Cohen, W. M., y Levinthal, D. A. (1989). Innovation and learning: the two faces of R & D. The economic journal, 99(397), 569-596. https://doi.org/10.2307/2233763

Crespi, G. y Zúñiga, P. (2012). Innovation and productivity: evidence from six Latin American countries. World development, 40(2), 273-290. https://doi.org/10.1016/j.worlddev.2011.07.010

Edquist, C. (1997). Systems of innovation: technologies, institutions, and organizations. Psychology Press.

Freeman, W. J. (1987). Simulation of chaotic EEG patterns with a dynamic model of the olfactory system. Biological cybernetics, 56(2-3), 139-150. http://dx.doi.org/10.1007/BF00317988

Gómez, M. C. y Borrastero, C. (2018). Innovación y heterogeneidad productiva en la Industria Argentina. Documentos de trabajo de investigación Facultad de Ciencias Económicas. (DTI-FCE), (1), 118. Disponible en: https://revistas.unc.edu.ar/index.php/DTI/article/view/19814. Consultado: 15/3/2022

Griffith R, Huergo E, Mairesse J, Peters B (2006) Innovation and productivity across four European countries. Oxford review https://doi.org/10.1093/oxrep/grj028 of economic policy 22(4):483–498.

Gutiérrez Rojas, C. y Baumert, T. (2018). Smith, Shumpeter y el estudio de los sistemas de innovación. Revista de Economía y Política 5(1), 93-111. Universidad Adolfo Ibañez, Chile. https://doi.org/10.15691/07194714.2018.003

Heijs, J. y Buesa, M. (2016). Manual de economía de innovación. Tomo I: Teoría del cambio tecnológico y sistemas nacionales de innovación. Instituto de análisis industrial y financiero. Universidad Complutense de Madrid. Disponible en: https://www.ucm.es/iaif/informacion-sobre-elinstituto-industrial-financiero. Consultado: 10/6/2022.

López, J. A. F., y Gómez, J. A. U. (2022). La innovación como factor decisivo de las organizaciones en países emergentes. Contaduría http://doi.org/10.22201/fca.24488410e.2022.2603 y Administración.

Lundvall, B. A. (1992). National systems of innovation: An analytical framework. London: Pinter.

Mairesse, J. y Mohnen, P. (2010). Using Innovation Surveys for Econometric Analysis. In Handbook of the Economics of Innovation (2), 1129-1155. North-Holland. https://doi.org/10.1016/S01697218(10)02010-1

Marín, A.; Liseras, N.; Calá, C. y Graña, F. (2017). Oportunidades de innovación divergentes: ¿es el territorio importante? Revista Pymes, Innovación y Desarrollo. 5(1), 2-23. Disponible en: 23. Disponible en: http://nulan.mdp.edu.ar/id/eprint/3057. Consultado: 10/4/2022.

Milesi, D.; Petelski, N. y Verre, V. (2011). The determinants of innovation: evidence from Argentine manufacturing firms. Documento de Trabajo N°3. Universidad Nacional de General Sarmiento.

Nelson, R. R., y Rosenberg, N. (1993). Technical innovation and national systems. National innovation systems: A comparative analysis, 1, 3-21.

OECD (2005). Oslo Manual - The Measurement of Scientific and Technological Activities. Proposed guidelines for collecting an interpreting technological innovation data, 30(162), 385-395.

Petelski, N.; Milesi, D. y Verre, V. (2017). Financiamiento público a la innovación: impacto sobre esfuerzos tecnológicos en pymes manufactureras argentinas. Revista Pymes, Innovación y Desarrollo, 5(3), 23-44. Disponible en: https://revistas.unc.edu.ar/index.php/pid/article/view/19659. Consultado: 7/3/2022.

Rabe-Hesketh S. and Skrondal A. (2012) Multilevel and Longitudinal Modeling Using Stata. Third edition. StataCorp LP.

Raffo, J.; L'huillery, S. y Miotti, L. (2008). Northern and Southern Innovativity: a comparison across European and Latin American Countries. European Journal of Development Research, 20(2), 219-239. https://doi.org/10.1080/09578810802060777

Sarmiento Paredes, S., Nava Mozo, V., Carro Suárez, J., y Hernández Cortés, C. (2018). Estudio comparativo de los factores de innovación en la pequeña y mediana empresa de manufactura textil. Contaduría y administración, https://doi.org/10.22201/fca.24488410e.2018.1268

Schumpeter, J. (1939). Business cycles. New York: McGraw-Hill.