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Innovation and productivity in developing countries: A study of Argentine manufacturing firms' behavior (1992–2001)☆

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Abstract

Following the methodology employed in studies for industrialized countries and using panel data from innovation surveys in Argentina with information for 1992–2001, this paper contributes to the nascent literature that analyzes the determinants of innovative inputs and outputs and their impacts on manufacturing firms' productivity in developing countries. The econometric results show that in house R&D and technology acquisition expenditures have positive payoffs in terms of enhanced probability of introducing new products and/or processes to the market. In turn, innovators attain higher productivity levels than non-innovators. The results also show that large firms have a higher probability of engaging in innovation activities and of becoming innovators.

JEL classification: L60; O31; O32

Keywords: Innovation; R&D; Technology acquisition; Productivity

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1. Introduction

The fact that innovating is a key element in firms' performance is well established in developed countries. Studies based in the European Community Innovation Surveys (CIS), among other sources, made it possible to learn in a more precise way about the factors influencing the innovation process and to measure the impact of innovation on performance.[1]

In contrast, the relevance of the innovation process in firms doing business in developing countries is not always properly acknowledged, especially by mainstream economists, who tend to assume that openness and easy access to foreign technology sources is all that matters in terms of fostering firms' productivity. It is no surprise, then, that there is a lack of detailed studies on the subject, especially after the application of deep structural reforms in the 1990s.

The main purpose of this paper is to contribute to fill that gap using data from two innovation surveys that describe the technological behavior and performance of Argentine manufacturing firms during a 10-year period: 1992–2001.[2] During that period, Argentina had high GDP growth in 1991–1994 (interrupted by the Tequila crisis in 1995) and in 1996–1998. In late 1998, the economy entered into a stagnation period that was followed by a deep fall in GDP in 2001 and 2002, in the middle of a huge financial and institutional crisis.

After the adoption of a currency board (the so called Convertibility Plan) and of a far-reaching program of structural reforms in the early 1990s, manufacturing firms – that were mostly born during the import substitution industrialization (ISI) phase – had to compete fiercely against the flow of imported goods in the expanding domestic market.

Large firms and, most notably, Transnational Corporations (TNCs) affiliates, were those that performed better in the new market conditions. In contrast, while many domestic firms went bankrupt or were sold to foreign investors, others totally or partially abandoned production activities to become importers of foreign goods.

Beyond the heterogeneity in their behavior and performance in the post-reform scenario, it could be expected that the best performing manufacturing firms (and especially the foreign owned and/or export oriented) would increase their investments in technology modernization to face the challenges coming from trade liberalization.

This was in fact what happened, as revealed by the first national survey on innovation activities in manufacturing firms carried out in 1997 (INDEC-SECYT, 1998). In a context of booming sales and productivity, innovation inputs (including R&D activities, acquisition of capital goods related to innovation activities, as well as expenditures in training, consultancies, engineering and design) increased by almost 69% between 1992 and 1996 (from 2.97% in 1992 to 3.70% of total sales in 1996).

Among firms that augmented their innovation expenditures, the bias in favor of technology imports over domestic innovation expenditures that had traditionally characterized the conduct of Argentine manufacturing firms in the past was, if anything, reinforced. Hence, in spite of an increase in in-house R&D and innovation expenditures, during the high-growth period inputs from abroad – mainly in the form of capital goods imports and foreign direct investment (FDI) inflows – were the main source of technological modernization for the manufacturing sector.

Besides increasing their innovation expenditures during this period, manufacturing firms were also very active introducing new product and process technologies. This comes as no surprise considering both the need to compete in a more open and deregulated economy as well as the technological lag that had been accumulated during the previous decade, in a scenario in which the Argentine beconomy was closed, stagnating and highly volatile.

What happened when the growth cycle was over? In the adverse conditions that prevailed since 1998, one would have expected a severe reduction in innovation activities, in a context in which firms were trying to cut expenditures and postpone investment decisions in order to face the recession. This presumption was confirmed by the second innovation survey (INDEC-SECYT-CEPAL, 2003), which showed that, in a context in which sales (as well as productivity and

[1] See Kleinknecht and Mohnen (2002).

[2] In a previous paper, a similar attempt was made with data for a shorter and very bad (in a macroeconomic sense) period: 1998–2001 (Chudnovsky et al., 2003).

investment) sharply fell, innovation expenditures had a drastic reduction (28.5%) between 1998 and 2001. Also expectedly, there were fewer firms introducing new technologies during this period. However, and unexpectedly, in house R&D expenditures augmented substantially (21.5%), although remained at modest levels.[3]

A number of relevant issues arise from Argentina's experience. In this paper we aim at answering the following questions:

(a) Which types of attributes and assets (i.e., size, ownership, market orientation, labor skills availability, etc.) make firms more prone to engage in innovation activities and to launch new products and new processes to the market?
(b) Do firms that engage in innovation activities have a higher probability of introducing a new product and/or process in the market? Furthermore, do in-house innovation activities have a different impact on the probability of becoming an innovator vis a vis technology acquisition expenditures?
(c) Do firms that introduce product and/or process innovations perform better than those that do not?

To answer these questions, we rely on data from the innovation surveys mentioned above and follow, to a large extent, the conceptual framework and methodology employed in several studies based on information from the European CIS. However, we make some adaptations to that methodology, in order to fit it to the reality of innovation activities in a country such as Argentina.

The paper is organized as follows. The conceptual and methodological issues arising from the received literature on the subject are discussed in Section 2. In Section 3, we report the basic features of the innovative behavior of Argentina's manufacturing firms during 1992–2001. Section 4 introduces the empirical methodology and econometric analysis. The conclusions are presented in the final section.

2. Innovation activities and firm performance: some conceptual and methodological issues

The availability of innovation surveys in the European Community and in other countries such as Canada in the 1990s has provided valuable information on several dimensions of the innovation process at the firm level. These dimensions had been previously outlined in the chain-linked model proposed by Kline and Rosenberg (1986) as well as in the national system of innovation (NSI) literature (Edquist, 1997). The rich information available from these surveys has also fostered new ways of doing research on key issues of the received literature on technological change, such as the determinants and consequences of innovation activities, while applying modern econometric techniques.

To analyze the information from these surveys, most recent papers have followed, in one way or another, the conceptual framework set by Crepon et al. (1998) (or CDM approach from now on).[4] Briefly, in this framework, innovation is considered as a process, which is carried out with specific inputs (R&D activities, and acquisition of embodied and disembodied technologies, among others) and by interacting with other firms and institutions. The innovative process should lead to certain outputs, which can take different forms. Most visible is a new or modified (for the firm or the market, yet not necessarily for the world) product. On the other hand, process innovations are also relevant, since they can improve the production process and make it more efficient. Finally, as innovation is not an end in itself, innovators (i.e. those firms which have launched new or improved products or processes) could be expected to have a better performance than non-innovators.

As illustrated in Fig. 1, in a first stage, there is a decision whether to allocate financial and human resources to innovation activities or not. Second, the amount of resources assigned provides a measure of the intensity of these activities at the firm level. In the third stage, there is (or should be) an innovative output (process or product innovations) related to the innovation intensity[5] and/or to some other features of

[3] Although it is not possible to differentiate between in house and external R&D in the first innovation survey, the second innovation survey has shown that 85% of the industry R&D expenditures during 1998–2001 were in house. Therefore, as a practical matter, throughout this work we refer to R&D expenditures as in house activities.

[4] Table A.1 of Appendix A lists and provides some details on recent papers that have followed the CDM framework.

[5] Undertaking innovation activities is not the same as being an innovator and for being an innovator is not always needed to have innovative expenditures. As we will see, this has been the case in

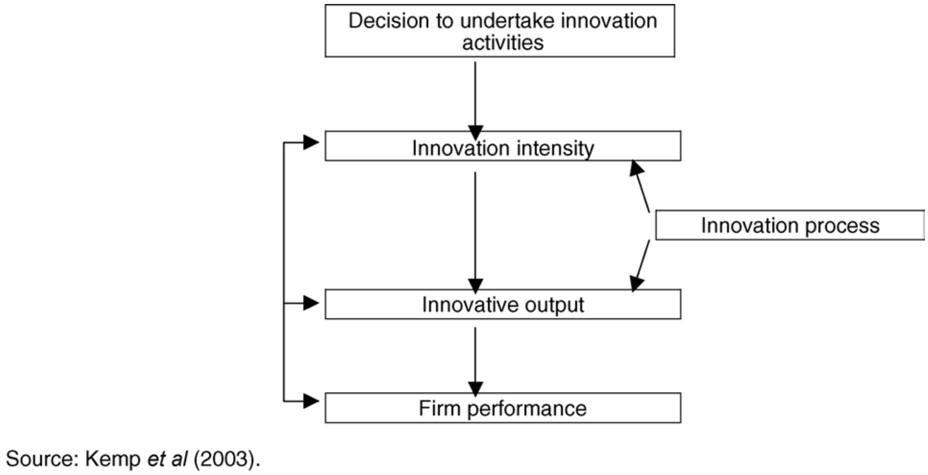

Fig. 1. The innovation process and firm performance.

the innovation process (such as interactions with different agents and institutions of the NSI). Finally, the firm's performance should be related to the innovative output.

Before introducing our analysis of the Argentine case, it is useful to describe how recent studies have approached and implemented this conceptual framework using data from innovation surveys. Besides presenting their main results,[6] we also discuss some of the most commonly used firm-level indicators of innovation inputs, outputs and performance.[7] This allows us to highlight the importance of introducing some adaptations to the prevalent methodology, in order to fit the CDM approach to the reality of innovation activities in a developing country such as Argentina.

In analyzing the determinants of innovation activities, recent papers have usually focused on evaluating the Schumpeterian hypotheses relating firm size to innovation efforts (Schumpeter, 1942).[8] In general, the evidence from innovation surveys has strongly supported that the probability of engaging in innovation activities increases with firm's size (typically proxied by total employment). On the other hand, there have been mixed results concerning the relationship between innovation intensity and size. For example, in a multi-country study, Lööf et al. (2001) found that firm size had a negative effect on innovation investment intensity in Finland, a positive effect in Norway and a non-significant effect in Sweden. In turn, Crepon et al. (1998) and Benavente (in press) found that although the probability of undertaking R&D activities increased with firm size, their intensity was independent of the latter (i.e. the elasticity of R&D expenditure to size was one).

The analysis of innovation activities has been restricted to R&D expenditures in most recent studies. In this regard, it is important to acknowledge two issues:

(i) Firms (especially SMEs) often make expenditures in informal innovation activities. These are usually hard to estimate but can be very relevant, especially in developing countries. Unfortunately, a large part of these activities may not be captured in innova-

Argentina. In addition, Crepon et al. (1996) report that only 20% of the near 10,000 French manufacturing firms in their sample that did some research in 1989 innovated between 1986 and 1990, while only 74% of all innovators performed some R&D. At least a part of these differences may arise from innovation activities that are not captured in the R&D indicator (see below).

[6] Kemp et al. (2003) and Kleinknecht and Mohnen (2002) provide additional details and results of recent papers that have followed this conceptual framework.

[7] The discussion of the main issues concerning the econometric modeling of the CDM approach is deferred until Section 4.

[8] See Cohen and Klepper (1996), Scherer (1992) and Kamien and Schwartz (1982).

tion surveys (hence, the impact of these informal activities cannot be assessed).[9]

(ii) While it may be understandable that studies for developed countries do not take into account (embodied and disembodied) technology acquisition when measuring innovative inputs, this should not be the case when analyzing firms' innovative behavior in developing countries, where external sources of technology are in general more significant than in house innovation activities. Since Argentina's innovation surveys included questions on the acquisition of technology, we are able to employ a broader measure of the innovation intensity at the firm level.[10]

Turning to the third stage of the CDM approach illustrated in Fig. 1, since the emergence of CIS surveys, a common trend in recent papers has been to measure firms' innovative output by the weight of new or significantly improved products on total turnover. Binary variables, indicating whether product and/or process innovations have been accomplished, are also used (which is the case of this study).

An advantage of these indicators is that they capture a direct link between the innovation effort and commercial success, as opposed to traditional patent indicators. In turn, besides its well-known limitation, the latter is of little use in the Argentine case, where manufacturing firms have obtained relatively few patents.[11] As a second advantage, the new innovative output indicators in innovation surveys capture not only "true" innovations, but products or processes that can be new for the firm but not for the industry (imitations), as well. This is a particularly important feature, especially in the case of developing countries, where most new products or processes are in fact imitations, even when introduced via licensing agreements or foreign direct investment.[12]

The share of innovative sales in total sales as indicator has been widely used in recent research. In general, the evidence points towards a positive and significant impact of innovation activities on innovative sales. Using data for French manufacturing firms and interval data for innovative sales, Crepon et al. (1998) estimated that a 10% increase in R&D intensity had an impact of almost 5% on innovative sales. In addition, based on the 1993 Canadian Survey of Innovation in manufacturing firms and using binary variables as innovation output indicators, Baldwin et al. (2002) estimated that the probability of introducing a product (process) innovation increased 24% (15%) in firms that engaged in R&D activities.

In turn, Lööf and Heshmati (in press) apply a version of the CDM model to Swedish data for the mid-1990s on both manufacturing and service firms. A distinctive feature of this study is the utilization of a comprehensive measure of innovation intensity, including spending on non-R&D based innovation activities, the purchase of outside services, machinery, and equipment for innovation activities, industrial design expense related to producing new products, training directly related to innovation activities, and some marketing expenses. The estimated return of such investment in terms of innovative sales suggested diminishing returns, with an elasticity of about one half.

However, it is worth mentioning that some studies have failed to find a positive relationship between innovative input and innovative output. Lööf et al. (2001) found it only in their Sweden sample, but in Finland and Norway no significant relationship was found. In addition, Benavente (in press) found that R&D did not contribute to innovative sales of Chilean manufacturing firms during 1995–1998.

The final stage of the CDM model analyzes the relationship between the innovative output and firms' performance. The latter has been captured through a variety of indicators, including labor productivity, value added and profits per employee. Naturally,

[9] For instance, activities that are a by-product of learning-by-doing processes. Besides, small firms may not be able to estimate the monetary or labor resources assigned to innovation activities since no dedicated department or team exists.

[10] A study on China takes explicitly into account these specific features of the innovative process in a developing country (Hu et al., 2003).

[11] According to INDEC-SECYT-CEPAL (2003), 98 firms registered 317 patents in 1998–2001. Only about 10% of the innovators obtained patents.

[12] In contrast, the main disadvantage of these recent indicators is that they are based on the respondent's own judgment (although survey questionnaires provide definitions on what is to be considered an innovation and what is not). A second caveat, shared with other innovation output indicators as well, is that the influence of organizational innovations as innovative outputs might not be fully captured (as long as they do not necessarily lead to new or improved products or processes).

the selection of the indicators generally depended not only on research objectives, but also on data availability.

The recent literature has usually reported a positive impact of innovations on performance. For instance, Crepon et al. (1998) estimated that a difference in innovative sales from the lowest share interval to the highest share (e.g. from 10% to 70%) corresponded to a 13% increase in value added per employee. In turn, analyzing Chinese manufacturing firms during 1995–1999, Jefferson et al. (in press) found that innovative sales were associated with greater productivity and profitability, especially in larger state-owned firms and local government collectives. However, Benavente (in press) found that firm productivity was not affected by innovative sales in the Chilean case.

3. Data sources and descriptive statistics

3.1. The data

With the purpose of analyzing the magnitude and diffusion of innovation activities in the Argentine manufacturing industry, two innovation surveys (designed in accordance with the methodology suggested by the Oslo and Bogotá Manuals[13]), were carried out by INDEC (Argentina's National Statistical Institute).

While the first survey covered the period 1992–1996 and included 1639 firms (INDEC-SECYT, 1998), the second survey collected information for 1688 firms during 1998–2001 (INDEC-SECYT-CEPAL, 2003). Both samples were randomly drawn from the National Economic Census of 1993 and from the Input–Output Matrix survey of 1997, respectively. In this way, they were intended to be representative samples of the manufacturing industry at the beginning of the periods they covered.

In addition, an important feature of the Argentine innovation surveys is that, as opposed to the European CIS, both innovators and non-innovators were required to answer the whole questionnaire—in particular, to report innovation expenditures. This avoids the selectivity problem in CIS surveys acknowledged in CDM (1998),[14] and has implications on the econometric strategy chosen in this paper, discussed below.

The data set used in the empirical analysis presented in this study is based on matched information for a panel of 718 firms interviewed in both the 1992–1996 and 1998–2001 innovation surveys.[15] In other words, our analysis is restricted to the subset of firms that were sampled only in both surveys, a balanced panel data set. As explained below, this decision allows firm fixed effects estimation, since key variables (most notably, the innovation output information) are not reported on a year-by-year basis, but only once for the period being covered by each survey.

Before presenting the data, it is important to discuss whether our empirical analysis is likely to be affected by sample selection (i.e. non-random sample biases), which generally arises if the sampling mechanism is related to unobservable firm characteristics.[16] In particular, our concern is on the possibility that unobserved attributes might have made firms in this sample perform significantly better than the population of manufacturing firms during 1992–2001. In our view, potential biases could arise in either two ways.

First, it could be argued that, even if innovation surveys were representative samples of the manufacturing industry during the 1990s (discussed below), excluding firms that were not sampled in both surveys implies that our analysis focuses on a subset of possibly best performers in the industry, which were self-selected into the sample as a consequence of unobservable attributes.[17] We have checked whether this source of bias seems likely by estimating a simple model of labor productivity – which is the measure of firm performance available in the Argentine innovation

[13] OECD (1997) and RICYT (2001), respectively.

[14] In CIS surveys, firms are first asked whether they have introduced a new product or process during 1998–2000, or whether they had any ongoing or abandoned activities to do so during this period. Only if they answer positively to one of these questions, they are asked additional information about their innovation outcomes, their R&D expenditures and other characteristics.

[15] These firms account for 29% of sales, 27% of employment and 24% of exports of the manufacturing sector in 1992–1996. For the 1998–2001 period, the figures are 27%, 20% and 19%, respectively.

[16] For a discussion of sample selection and attrition in panel data sets, see Wooldridge (2001) pp. 577–590.

[17] In turn, a non-zero correlation between these attributes and the explanatory variables of interest in our study would make estimation results based on the balanced panel not consistent.

surveys – and comparing results based on the balanced and unbalanced panel data sets. As shown in Table A.4 in Appendix A, the magnitude of the estimated coefficients and standard errors are very similar. Thus, we conclude that estimation results are robust in the balanced panel estimation and that this source of selection bias, if present, is not likely to have an important impact on our conclusions.

Actually, this result is not surprising, since innovation surveys in Argentina were not designed or intended to follow a group of firms over time, but only to obtain a representative sample from the universe of manufacturing firms in the Argentine industry for the period they covered.[18] In fact, since the samples of firms considered in each survey were obtained from two different sources (as explained above), innovation surveys in Argentina conform to a rotating panel and the decision to sample firms in both surveys may be safely regarded as being random. In other words, since panel rotation was the main reason to drop firms in a matching between both surveys, this would not by its own add a significant bias to results.

As a second (and probably more serious) source of bias, it is possible that innovation surveys are by definition introducing a selection bias, arising from the fact that firms actually surveyed are those that survived over the entire period covered by each survey. Although, as stated above, both surveys were intended to be representative samples of the manufacturing industry at the beginning of the periods they covered, firms that closed (e.g. through bankruptcy) during those periods were not surveyed, hence it was not feasible to include them in our study. Unfortunately, it is not possible to check the magnitude of this bias without merging our data set with additional sources of information, which are not available. In this way, although not a testable hypothesis, it is not unlikely that firms included in the innovation surveys were actually among the best performing ones at the beginning of the period or at least those that had larger probabilities of survival.[19]

Overall, we consider that it is the second source of selection bias mentioned, and not the first one, the one that might raise a concern on the adequacy of generalizing our conclusions to the whole of the manufacturing industry during the 1990s. Therefore, it seems judicious to acknowledge that the conclusions that we draw from our empirical analysis are valid only for this subset of firms (which, nevertheless, accounts for a significant share of the industrial activity during the 1990s).[20]

3.2. Descriptive statistics

While most of the firms that compose our data set, 69%, were created before 1975 – hence, they were born during the ISI phase – only 7% were created during this decade. However, more than 50% of the firms created before 1975 changed ownership. These changes occurred mostly in the 1990s and generally involved the acquisition of indigenous firms by TNCs.

SMEs and domestic firms accounted for the majority of the 718 firms. In both 1996 and 2001, 582 firms (81% of the sample) employed less than 300 employees. On the other hand, the share of foreign firms (i.e. firms with a share of foreign capital larger than 10%) increased from 11% in 1996 to 19% in 2001.[21]

In Table 1 National Classification of Economic Activities, it can be appreciated that food and beverages, chemicals, textiles, and machinery and equipment sectors accounted for almost one half of the firms. While natural resources intensive sectors accounted for almost one third of the firms, R&D intensive was the least numerous group.[22]

The performance of manufacturing firms was irregular throughout the 1990s. Considering the evolution of labor productivity (measured by sales per employee), Table 2 shows that, between 1992 and 1998, surveyed firms experienced a period of high growth (37%), while

[18] This implies that firms surveyed in the first survey but missing in the second are not necessarily those that went bankrupt (or, in general, the worst performers in the industry). In the same way, firms that were first surveyed in the second survey are not necessarily newly born firms (i.e. inexistent during the period covered by the first survey).

[19] It is nonetheless important to remark that this concern is likely to be attenuated by the relatively high response rates recorded in both surveys. In fact, a distinctive attribute of the innovation surveys in Argentina, response rates reached 70% and 76% in the first and second surveys, respectively. In comparison, the European CIS did not attain 30%.

[20] See endnote 15.

[21] Since our data set focuses on the evolution of a given group of firms over time, this fact reflects the acquisition of domestic firms by foreign investors.

[22] The classification of sectors into R&D, scale, labor and natural resources intensive was developed by Pavitt (1984) and later adapted by Guerrieri and Milana (1989).

Table 1
Distribution of firms according to sectors

	Sector (CLANAE classification)	All firms		Innovators (1992–1996)		Innovators (1998–2001)	
		Firms	%	Firms	%	Firms	%
Scale intensive	Rubber and plastics	46	6.4	38	6.6	32	7.5
	Common metals	24	3.3	20	3.5	18	4.2
	Metal products	39	5.4	30	5.2	19	4.5
	Machinery and equipment	59	8.2	53	9.2	42	9.9
	Radio and TV equipment	9	1.3	8	1.4	8	1.9
	Vehicles	31	4.3	30	5.2	22	5.2
	Other transport equipment	10	1.4	6	1	2	0.5
Scale		218	30.4	185	32.1	143	33.6
Labor intensive	Textiles	67	9.3	47	8.2	25	5.9
	Wearing	15	2.1	10	1.7	7	1.6
	Leather and footwear	13	1.8	11	1.9	10	2.4
	Edition and printing	38	5.3	32	5.6	18	4.2
	Furniture	27	3.8	19	3.3	12	2.8
Labor		160	22.3	119	20.7	72	16.9
R&D intensive	Chemicals	75	10.4	65	11.3	55	12.9
	Electrical machinery	24	3.3	22	3.8	17	4
	Medical instruments	10	1.4	7	1.2	6	1.4
R&D		109	15.2	94	16.3	78	18.4
Natural resources intensive	Food and beverages	144	20.1	114	19.8	83	19.5
	Tobacco	1	0.1	1	0.2	1	0.2
	Wood	21	2.9	9	1.6	5	1.2
	Paper	21	2.9	18	3.1	13	3.1
	Petroleum	6	0.8	6	1	5	1.2
	Fabricated and non-ferrous minerals	38	5.3	30	5.2	25	5.9
Natural resources		231	32.2	178	30.9	132	31.1
Total		718	100	576	100	425	100

the opposite occurred during 1998–2001 (−12%). In turn, total employment showed a steadily decreasing trend throughout these years. In 2001, the average number of employees in manufacturing firms was 20% smaller than in 1992. However, there was a significant composition effect, since the weight of skilled labor (the share of professionals in total employment) increased without interruption throughout the 1990s, from 6.8% in 1992 up to 8.7% in 2001.

In addition, throughout the decade, a larger share of firms imported than exported (e.g. 73% and 60%, respectively, in 1996). However, as a share of sales, the intensity of these activities was similar between importers and exporters (see Table 2). This trend changed in 2001 when, affected by the domestic recession that began in 1998, the intensity of imports decreased significantly, as opposed to exports.

Turning to innovation activities, total expenditures figures (reported in Table 2) include not only R&D and technology acquisition, but also management, engineering and industrial design investments related to innovation activities. As already mentioned, this broad definition is desirable for analyzing innovation activities in developing countries such as Argentina. Table 2 shows that, after increasing in 1992–1996, the number of firms engaged in innovation activities (i.e. firms with positive innovation expenditures) decreased markedly – from 59% to 45% – during 1996–2001. Furthermore,

Table 2
Performance and innovation activities—718 firms

	1992		1996		1998		2001	
	Average[a]	%[b]	Average[a]	%[b]	Average[a]	%[b]	Average[a]	%[b]
Performance								
Sales/employment 1992 = 100	100		127		137		122	
Growth (%)			27		8		−12	
Employment 1992 = 100	100		93		91		80	
Skilled labor/employment (%)	6.8	75	7.4	75	7.7	76	8.7	77
Exports/sales (%)	14	44	15	60	17	51	19	54
Imports/sales (%)	14	64	15	73	18	62	15	60
Innovation activities[c]								
R&D	0.89	22	0.83	29	0.86	25	0.94	28
Technology acquisition	4.99	28	4.22	45	4.26	33	2.82	31
Total expenditures	3.93	46	4.08	59	3.91	45	3.04	45

Source: Own calculations based on data from the Argentine Innovation Surveys.
[a] Calculated for firms that report a positive value of the respective variable.
[b] Percentage of firms that report a positive value of the respective variable.
[c] Expenditures as a percentage of total sales.

among these firms, the intensity of total expenditures on innovation activities decreased to almost 3% of total sales in 2001, from a maximum higher than 4%, reached in 1996.

This trend is explained largely by the main component of innovation expenditures during the decade, which was the acquisition of technology external to the firms. The latter includes capital goods (related to innovation activities within the firm) and technology transfer (patent rights, licenses, trademarks, designs) acquired domestically or abroad. After a substantial growth during 1992–1996, the share of firms that invested in technology acquisition decreased markedly (from 45% in 1996 to 31% in 2001). At the same time, the intensity of these expenditures decreased from 5% in 1992 to 2.8% in 2001.

However, Table 2 shows that the share of firms that undertook R&D activities increased from 22% to 28% in 1992–2001. Moreover, the intensity of R&D expenditures among these firms also increased, reaching 0.94% of total sales in 2001.[23]

Before turning to the comparison between innovators and non-innovators, it is important to emphasize that, for the purposes of this paper, a firm is considered

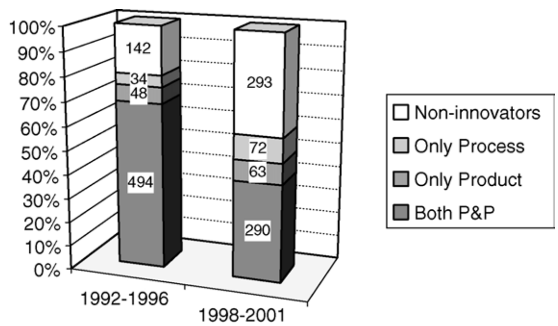

Fig. 2. Classification of firms according to their innovative output.

an innovator during 1992–1996 (or 1998–2001) if it introduced new or radically modified products and/or processes during that period.[24] In other words, a firm is defined as an innovator depending on the outcome (or output) of its innovation process and not on whether it has undertaken innovation activities—which, as described in Fig. 1, are inputs to this process. In fact, not every innovator reported innovation expenditures, and vice versa (see below).

Fig. 2 shows that while most firms (80%) were innovators in 1992–1996, the number of them decreased notably during 1998–2001, though still accounted for

[23] R&D expenditures augmented in absolute figures, as well. As mentioned in the introduction, between 1998 and 2001, R&D in the industry increased by 21.5% (INDEC-SECYT-CEPAL, 2003).

[24] As explained in Section 2, a firm's innovation can be new to either the market or the firm.

Table 3
Performance in innovators and non-innovators

	1992		1996		1998		2001	
	Average[a]	%[b]	Average[a]	%[b]	Average[a]	%[b]	Average[a]	%[b]
Innovators								
Sales/employment 1992 = 100	100		130		146		130	
Growth (%)			30		12		−11	
Non-innovators[c]	1.36		1.62		1.34		1.36	
Employment 1992 = 100	100		94		109		96	
Skilled labor/employment (%)	6.9	81	7.5	82	8.5	85	9.6	87
Exports/sales (%)	13	49	15	67	16	64	18	67
Imports/sales (%)	14	71	15	80	16	76	15	74
Non-innovators								
Sales/employment 1992 = 100	100		110		145		126	
Growth (%)			10		31		−13	
Innovators[c]	0.74		0.62		0.75		0.73	
Employment 1992 = 100	100		83		89		76	
Skilled labor/employment (%)	6.2	53	6.6	51	6.3	64	6.9	63
Exports/sales (%)	18	20	16	34	18	32	23	35
Imports/sales (%)	11	33	11	42	20	41	15	40

Source: Own calculations based on data from the Argentine Innovation Surveys.
[a] Calculated for firms that report a positive value of the respective variable.
[b] Percentage of firms that report a positive value of the respective variable.
[c] Quotient of average sales per employee between innovators and non-innovators.

59% of the sample. Even though these figures may appear surprisingly high at a first glance, it is important to take into account that the European CIS reported that 50% of European manufacturing firms had introduced a product or process innovation during 1990–1992 (Archibugi and Sirilli, 2000), a shorter period than those covered by the Argentine surveys. Furthermore, as stated in the introduction, it cannot be ignored that, since the implementation of a program of structural reforms in the early 1990s, the Argentine industry has been radically transformed, inducing firms to adopt new strategies (to innovate, among them) to be able to survive.

When innovators are classified according to the type of innovations reported (only products, only processes or both products and processes), we can observe a significant change in the composition of this group. In particular, Fig. 2 shows that the share of firms that introduced both products and processes fell between the two periods analyzed (from 86% to 68% of innovators).

In general, the group of innovators has a larger presence of large and foreign firms than the whole sample. In 2001, for example, SMEs represented 75% of innovators, while foreign firms accounted for 24%. Furthermore, Table 3 shows that innovators reached labor productivity levels that were, at least, 1.3 times higher than in non-innovators. Nevertheless, productivity growth rates were similar in both groups.

This was not the case for employment, with non-innovators reducing labor considerably faster than innovators.[25] The share of skilled labor has also been higher in the latter. For example, in 2001, while skilled labor accounted for almost 7% of total employment in non-innovators, this figure was 10% in innovators (the gap in the use of skilled labor between both groups increased during the period under analysis). Table 3 also shows that innovators were more involved in international trade during the 1990s. In 2001, while 67% of these firms exported, only 35% of non-innovators did so (although export intensities have been lower in innovators). In the case of imports, these percentages were 74% and 40% in 2001, respectively.

Table 4 shows that the majority of innovators engaged in innovation activities. Moreover, this share

[25] Hence, although labor productivity increased approximately at the same rate in both groups, it seems that this result was mainly attained by market expansion among innovators, while non-innovators resorted to labor force reductions.

Table 4
Innovation expenditures in innovators and non-innovators

	1992		1996		1998		2001	
	Average[a]	%[b]	Average	%[b]	Average	%[b]	Average	%[b]
Innovators								
R&D	0.89	27	0.84	35	0.87	40	0.93	45
Technology acquisition	5.03	33	4.10	53	4.29	50	2.79	50
Total expenditures	3.93	55	4.00	69	4.00	68	3.06	70
Non-innovators								
R&D	0.70	1	0.40	3	0.70	3	1.20	4
Technology acquisition	4.20	7	5.90	16	3.90	7	3.30	4
Total expenditures	3.80	9	5.40	19	3.00	10	2.80	8

Source: Own calculations based on data from the Argentine Innovation Surveys.
[a] Calculated for firms that report a positive value of the respective variable.
[b] Percentage of firms that report a positive value of the respective variable.

increased considerably during the period analyzed (from 55% in 1992 to 70% in 2001). Equivalently, these figures indicate that a minor (though significant) number of firms introduced innovations without making innovation expenditures.[26] In contrast, expectedly, the share of non-innovators that engaged in innovation activities was relatively small, except in 1996 (see Table 4).[27] In other words, relatively few manufacturing firms allocated resources to R&D and/or technology acquisition without introducing innovations during the 1990s.

In turn, the data in Table 4 show that the intensity of innovation expenditures was similar between innovators and non-innovators during the 1990s. In other words, innovative firms that engaged in innovation activities did not allocate higher investment efforts than non-innovators that also undertook these activities. Tentatively, the data suggest that, in order to explain which firms became innovators during the last decade, it might be more relevant to consider whether firms engaged in innovation activities or not, rather than emphasizing the intensity with which these activities were undertaken. In fact, we follow this approach in the econometric modeling in the next section.

4. Econometric analysis and results

Within the CDM framework illustrated in Fig. 1, this section analyzes the innovation activities and performance of Argentine manufacturing firms during 1992–2001. The econometric analysis is based on the panel of 718 firms described above.

We begin by presenting the estimation strategy and the specification of the empirical model. Subsequently, the main findings are discussed. Tables with the econometric results and definitions of the variables included in the regressions are found in Appendix A.

4.1. Estimation strategy

It is worth noting that by focusing on this group of firms, we are able to use panel data techniques in the econometric exercises.[28] Using firm-specific fixed effects estimators is of utmost importance for our purposes, since they allow us to control for time invariant unobserved heterogeneity at the firm level and, in this

[26] Although the data do not allow us to identify the reasons behind this fact, we can suggest two explanations: (i) innovations may had been the result of expenditures in previous years, which were discontinued during the period when the introduction of these innovations occurred; (ii) innovations may had been the result of informal innovation activities not properly captured by the survey questionnaire.

[27] Tentative explanations for this fact are: (i) the existence of lags between the investment in innovation and its yield; (ii) the possibility that innovation expenditures were directed to objectives other than introducing new products or processes, such as reduction of costs or minor adaptations of existing products and processes.

[28] Otherwise, as stated above, this would have been impossible since the data on innovative output is not reported on a year-by-year basis, but only once for the period being covered by each survey.

way, deal with a potential source of endogeneity in our estimations.[29]

In fact, the problem of simultaneity (or, more generally, endogeneity) in the estimation of the CDM model, represented by Eqs. (1)–(4) below, has been widely acknowledged in the literature since CDM (1998). Briefly, in that paper, the authors estimate all equations simultaneously using a two-step procedure that requires introducing exclusion restrictions in order to obtain instruments and achieve identification of the structural parameters.[30] Besides imposing some a priori structure on the model (at the risk of misspecification errors), the estimation strategy in CDM (1998) does not fully tackle the endogeneity problem. The reason is that the key exogeneity condition (i.e. whether the instruments are correlated or not with unobservables) is not discussed, but assumed away.[31]

In this paper, we have followed the same conceptual framework, but employ a different empirical methodology for analyzing the different stages of the CDM approach. Given that our data set does not provide us with valid exogenous instruments, our (second best) strategy is to take advantage of the panel data structure (using fixed effects estimators), in order to be able to control for unobservable heterogeneity at the firm level. For example (unobserved) management quality or entrepreneurship are firm characteristics that could have affected both innovation activities and outcomes, generating endogeneity in cross-sectional estimations. However, to the extent that these unobservables remained roughly constant between 1996 and 2001, fixed effects estimation is a feasible alternative for obtaining consistent parameter estimations.

Naturally, this estimation method does not control for firm-specific time-varying unobserved effects that are correlated with the regressors.[32] Nevertheless, we are able to include a time dummy in order to control for unobservable effects that could have affected all firms over time (for example, different macroeconomic contexts during 1992–1996 and 1998–2001). Furthermore, surveyed firms are also classified into four groups (labor, scale, R&D and natural resources intensive), allowing us to model sectoral trends and control for changing availability of sectoral technological opportunities over time (see Table 2).

Finally, we prefer to estimate the equations of the CDM model separately, instead of using system estimators.[33] The reason, which is in line with our previous discussion, is that although system estimators are generally more efficient than equation-by-equation methods, they require stronger exogeneity assumptions if they are to provide consistent estimations (i.e. the regressors need to be uncorrelated with disturbance terms in all of the equations of the system). In this way, we explicitly favor robustness instead of efficiency in our estimations.

Matching existing innovation surveys with exogenous data that could provide valid instruments is a way in which this endogeneity problem may be tackled in the future. Nevertheless, it could be even more important if the empirical framework in CDM were complemented by theoretical results that provided solid guidelines for choosing instruments or exclusion restrictions in system estimators, in order to enhance the soundness of recent findings.

4.2. Model specification

As presented in Fig. 1, the CDM approach involves analyzing three relationships, the first of them being the link between innovation expenditures and its determinants. As shown in Table 4, a significant proportion of the surveyed firms did not undertake innovation activities (41% in 1996 and 55% in 2001). Thus, a natural approach to take account of this fact is to model

[29] The other popular panel data estimator, the random effects estimator, does not allow for arbitrary correlation between the fixed effect and the regressors. In fact, for consistent estimation, it requires even stronger exogeneity assumptions than a pooled OLS estimator. For this reason, random effects estimations are not reported in this study. Nevertheless, Hausman specification tests of our panel data regressions (on labor productivity and innovation intensity), are reported later in this section.

[30] For example, CDM (1998) assumes that the share of skilled labor directly affects firm productivity, but not the production of innovations. In addition, it is assumed that the market share does not enter directly in the innovation output equation, although it is an explanatory variable of innovation activities.

[31] See Wooldridge (2001), chapter 9, for a discussion of these issues in simultaneous equation models.

[32] This explains why we consider the fixed effect estimation a second best strategy, given the unavailability of valid exogenous instruments.

[33] For an overview of estimations procedures commonly used in the recent literature on innovation, see Table A.1 in Appendix A.

expenditures in innovation activities as a corner solution outcome model—i.e. firms solving an optimization problem, and for some of them their optimal expenditure in innovation activities is zero.

In these models, the response variable takes on the value 0 with positive probability but it is a continuous random variable over strictly positive values. As opposed to the censored regression and sample selection models (which have been routinely employed in the analysis of the CIS surveys), it is essential to understand that, in corner solution applications, data observability is not an issue for us. As stated in the previous section, this is the case of our data set, in which we observe the amount of innovation expenditures for every firm (innovators and non-innovators) in the sample.[34]

Under these circumstances, as an alternative to the standard corner solution model – the Tobit model – we prefer a two-tiered model that allows the decision to engage in innovation activities and its intensity to be explained by different mechanisms (see Wooldridge, 2001, p. 536). In addition, this model is easily extended to include fixed effects. For firm $i = 1, \ldots, 718$, in sector $j = 1, \ldots, 4$ and period $t = 1, 2$ (1996 and 2001), the equations are:

$$D_{ijt} = \begin{cases} 1 & \text{if } \alpha^1 + \varphi^1 X^1_{ijt} + \text{time01}^1 + \text{trend}^1_{jt} + \mu^1_i + \varepsilon^1_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$E_{ijt} = \alpha^2 + \varphi^2 X^2_{ijt} + \text{time01}^2 + \text{Trend}^2_{jt} + \mu^2_i + \varepsilon^2_{it}, \quad \text{if } E_{ijt} > 0,\ t = 1, 2 \quad (2)$$

where D_{ijt}: decision to engage in innovation activities. Dummy variable equal to one if firm i in sector j reported positive innovation expenditures in period t; E_{ijt}: is the intensity of innovation expenditures (including R&D and technology acquisition expenditures), in log; X^g_{ijt}: vector of firm specific control variables[35]: size (Size), interaction of size and time dummy (tsize), dummy for being part of a group of firms (Group), labor skills (Skills), exports (Expo) and nationality (FDI10) for equation $g = 1, 2$ *time01*^{g}: time dummy equal to one if $t = 2$ (i.e. if the observation corresponds to the period 1998–2001) and zero if $t = 1$ (i.e. if the observation corresponds to 1992–1996), $g = 1, 2$; Trend^g_{jt}: sector specific trend, equal to the product of time01_g and vector sec_j (set of dummy variables for labor, natural resource, R&D and scale intensive sectors introduced in Table 1); μ^g_i: unobserved firm specific fixed effect, $g = 1, 2$; ε^g_{it}: unobserved disturbance term, $g = 1, 2$.

Eq. (1) dictates the probability that innovation expenditures are zero or positive. For estimation, we assume that (conditional on the regressors and the fixed effect) the probability of undertaking innovation activities follows a logistic distribution. Under this assumption, we are specifying a conditional fixed effects logit model, which makes it possible to obtain parameter estimations without imposing any assumption about how the unobservable fixed effect μ^1_i is related to the regressors in Eq. (1).[36]

In turn, Eq. (2) states that, conditional on being positive, innovation expenditures follow a linear panel data model. Therefore, under this assumption, consistent parameter estimations can be obtained using a standard fixed effects estimator.[37]

In a second stage, the CDM approach focuses on the impact of innovation activities on the innovation output of the firms. As in the previous section, innovation inputs are classified into R&D and technology acquisition. Besides, firms are divided into continuous and non-continuous R&D performers.[38]

[34] Although not reported, a generalized Tobit model was estimated using the two-step procedure developed by Heckman (1979). As expected, after evaluating the significance of the inverse Mills ratio, we confirmed that the absence of selection bias in R&D expenditure could not be rejected at conventional levels (p-value was 0.880).

[35] Following CDM (1998), without good a priori reasons to do otherwise, we actually include the same set of control variables in both equations. Thus, $X^1_{ijt} = X^2_{ijt} = X_{ijt}$. The exact definition of these variables is provided in Table A.2 of Appendix A.

[36] See Wooldridge (2001), chapter 15 for an introduction to this model.

[37] We performed a Hausman test of the appropriateness of the random-effects estimator. The p-value for evaluating the null hypothesis (i.e. that the difference in estimated coefficients is not systematic) was 0.1148. Thus, we found it more secure to work with and report only the fixed effects estimation results.

[38] A firm is considered a continuous R&D performer in a given period (1992–1996 or 1998–2001) if it reports positive R&D expenditures in every year of it (see Table A.2).

Furthermore, we intend to provide additional insight by inquiring for differences not only among innovators and non-innovators, but also among different kinds of innovators (as described in Fig. 2). Our data set provides binary data on the introduction of new (or improved) product and/or process innovations. Therefore, a natural approach to model the outcome of the innovation process at the firm level is to specify a multinomial logit (MNL) model, with response probabilities:

$$P(\mathrm{TYPE}_{it} = k_{it}|I_{it}, X_{ijt}) = \frac{\exp(\beta^k I_{it} + \varphi^k X_{ijt})}{1 + \sum_k \exp(\beta^k I_{it} + \varphi^k X_{ijt})}, \qquad k = B, C, D \tag{3}$$

Besides, a usual identification restriction in the MNL model is to define a base category or "comparison group", by setting its parameters equal to 0. In our case, the comparison group is non-innovators. Thus, $\beta^N \equiv \varphi^N \equiv 0$, and

$$P(\mathrm{TYPE}_{it} = N_{it}|I_{it}, X_{ijt}) = \frac{1}{1 + \sum_k \exp(\beta^k I_{it} + \varphi^k X_{ijt})}, \qquad k = B, C, D \tag{3'}$$

where TYPE_{it}: unordered response variable that indicates the outcome of the innovation process in firm i during period t, classifying it either as a non-innovator (N), both product and process innovator (B), only process innovator (C), or only product innovator (D); I_{it}: vector of dummy variables indicating innovation activities in firm i during period t. These activities are continuous R&D (RDc_{it}), non-continuous R&D (RDn_{it}) and technology acquisition (TA_{it})[39]; X_{ijt}: includes a vector of firm specific control variables (size, dummy for being part of a group, labor skills, exports and nationality), a constant term, a time dummy, 4 sectoral trends – defined in Eqs. (1) and (2) – and 21 dummies to include sector fixed effects (see Table 1).

Finally, the third stage of the CDM model involves the fixed and random effects estimation of the impact of the innovative output on firms' performance.[40] Therefore,

$$Y^4_{ijt} = \alpha^4 + \beta^4 Z^4_{ijt} + \varphi^4 X^4_{ijt} + \mathrm{time01}^4 + \mathrm{Trend}^4_{jt} + \mu^4_i + \varepsilon^4_{it} \tag{4}$$

where Y^4_{ijt} is labor productivity of firm i in sector j during period t. Logarithm of sales of own products per employee; Z_{ijt}: set of three dummy variables indicating the outcome of the innovation process in firm i: prodproc, oproc or oprod equal to one if the firm innovated in both products and processes, only processes or only products during period t, respectively; X_{ijt}: includes firm-level control variables defined in Eqs. (1) and (2) and, in addition, a dummy IK_{ijt} for investment in physical capital goods[41]; $\mathrm{time01}_4$: time dummy equal to one if $t = 2$ (i.e. if the observation corresponds to the period 1998–2001) and zero if $t = 1$ (i.e. if the observation corresponds to 1992–1996); Trend^4_{jt}: sector specific trend, equal to the product of $\mathrm{time01}_4$ and vector sec_j (set of dummy variables for labor, natural resource, R&D and scale intensive sectors); μ^4_i: unobserved firm specific fixed effect; ε^4_{it}: unobserved disturbance term.

Next, the main results of our estimations are reported.

4.3. The decision to undertake innovation activities and the intensity of innovation

To begin with, as shown in Table A.3, the conditional fixed effects logit estimation (Eq. (1)) indicates that the size of the firm is a relevant explanatory variable in the first stage[42] of the CDM model. In accordance with the findings of recent studies, larger firms are more prone to be engaged in innovation activities.[43] In other words, innovation expenditures are, ceteris paribus, more difficult to undertake and to finance the smaller is the firm. The estimated increase in the probability of engaging

[39] The exact definition of these variables is provided in Table A.2 of Appendix A.

[40] As in the analysis of innovation expenditures, the reported results (Table A.3) are based in the fixed effects estimation, since a Hausman test (not reported) rejected the null hypothesis of the appropriateness of random effects (p-value was 0.0000).

[41] Argentine innovation surveys do not provide information on physical capital stock.

[42] Throughout this section, we characterize a variable as "statistically significant" if the p-value of its associated coefficient is smaller than 10%. Further details of the estimation results are found in Table A.3.

[43] In addition, since tsize^1 was not statistically significant, we found that this effect was constant during the period 1992–2001.

in innovation activities originated by a doubling of the number of employees in the median firm in our data set (from 104 to 208 employees) during 1998–2001 is 22.6% (from 38.7% to 61.3%).

On the other hand, our panel data analysis suggests that the relationship between the intensity of innovation expenditures and size is negative but not constant over the period analyzed (Eq. (2)). We find that the elasticity of innovation intensity to employment was 0.35 during 1992–1996 and 0.7 in 1998–2001.[44] However, the estimated elasticity for the last period is not statistically different from one.[45] In this way, the evidence points to decreasing and constant returns of innovation intensity to employment during the first and second periods analyzed, respectively.

In addition, our estimation results support the hypothesis that labor skills have a positive and significant impact on the probability of undertaking innovation activities, but not on their intensity. On the other hand, and somewhat unexpectedly, the dummies for exporters, foreign ownership and being part of a group, do not affect any of these stages of the CDM approach (see Table A.3).

Finally, although fixed effects estimation does not allow the inclusion of technological sector variables (because they are constant over time), their interaction with the time dummy reveals that the probability of initiating innovation activities during 1998–2001 increases, ceteris paribus, in firms operating in the natural resources intensive sector.

4.4. *The innovative output*

As mentioned above, the innovative output indicators are binary data that allow the estimation of the probability of introducing new products and/or processes during the years covered in the innovation surveys. Following the CDM approach, our objective

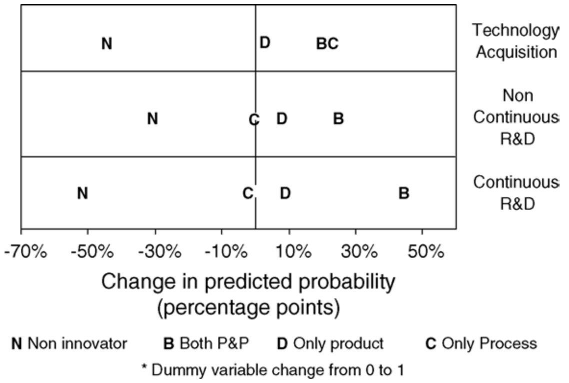

Fig. 3. Impact of innovation inputs on predicted probabilities of innovation output outcomes.

is to determine the impact of different innovation activities on the innovation output indicators. Thus, innovation inputs are classified as (continuous and non-continuous) R&D and external technology acquisition.

The estimation results of the MNL model in Eq. (3) are presented in Table A.3. Because of the non-linear characteristics of this model, estimated probabilities depend on the values at which other significant independent variables are being held constant. In this case, probability changes are calculated for a median sized firm that do not perform innovation activities and employ a median share of skilled labor during 98–01.[46] According to the estimations, a firm with these characteristics will not obtain innovations with a probability of 79%, while both product and process, only product and only process innovations will be obtained with probabilities of 10%, 3% and 8%, respectively.

Fig. 3 shows how predicted probabilities for each innovation output outcome (denoted by the letters N, B, C, D) are modified when the firm undertakes innovation activities (represented by dummy variable changes from 0 to 1, i.e. if the firm performs an innovation activity or not). To begin with, the three innovation inputs considered share a common feature: performing innovation activities considerably decreases the chances of not being an innovator. Nevertheless, this effect is larger for continuous R&D performers (with

[44] This result is obtained by adding the estimated coefficients associated to size ($size^2$) and to the interaction between the time dummy and size ($tsize^2$) variables in Eq. (2) (see Table A.3). Note that since both the dependent variable (innovation expenditures per employee) and size (total employment) are measured in logarithms, in order to obtain the elasticity of innovation intensity to employment, it is necessary to add one to the estimated coefficients in Table A.3.

[45] The *p*-value for testing the null hypothesis of $size^2 + tsize^2 = 0$ in Eq. (2) is 0.2992.

[46] Median values for total employees and share of skilled labor in our data set are 104 and 0.357, respectively.

the probability of not obtaining innovations being 26%, i.e. decreasing by almost 53% points).

Furthermore, performing R&D activities (particularly, in a continuous fashion) cause larger increases in the probability of obtaining both products and process innovations than technology acquisition. Fig. 3 also shows that the probability of obtaining only process innovations is only enhanced significantly by technology acquisition expenditures. This result might reflect the fact that the main component of technology acquisition during the 1990s was embodied technology, a key source of process innovations in the Argentine manufacturing industry.

While computing probability changes is a useful way to assess the magnitudes of the effects in the MNL model, it is limited in two ways (see Long, 1997). First, the discrete changes described above indicate changes for a particular set of values of the independent variables (i.e. for the median firm in our data set). Second, they do not indicate the dynamics among the innovation output outcomes (i.e. how a change in a certain independent variable affects the odds ratio between two different innovation outcomes). Both issues are tackled in Fig. 4, which plots the coefficients of the MNL model reported in Table A.3. The relative magnitudes of the effects of the innovation inputs are shown by the difference in the coefficients, i.e. the distance between the letters plotted in Fig. 4 (also, the lack of statistical significance at the 10% level is shown by a connecting line). Specifically, the difference in the coefficients captures the change in the logarithm of the odds ratio (quotient of probabilities) between two outcomes (i.e. $\log\left[\frac{p_j(I,\beta)}{p_h(I,\beta)}\right] = I(\beta_j - \beta_h)$), where I is the vector of innovation activities and p and β are, respectively, the probabilities and coefficients for the innovation output outcomes j and h.[47] The intuition is that if, for a given innovative input, the difference between two coefficients is not significant, then that variable does not differentiate the two outcomes (in the sense that their relative likelihood is not altered).

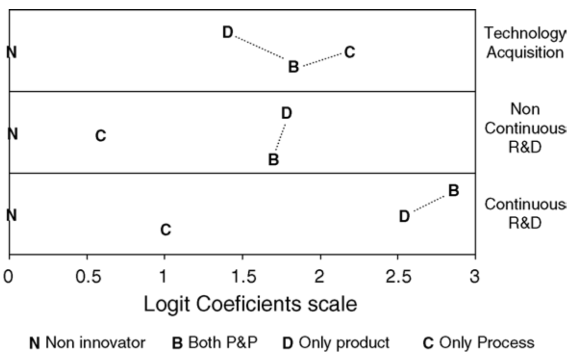

Fig. 4. Impact of innovation inputs the relative likelihood of innovation output outcomes.

The estimation reveals that R&D and technology acquisition have different impacts on the probability of becoming an innovator. On one hand, R&D activity increases the relative likelihood of both product and process and only product innovations against only process innovations.[48] On the other, technology acquisition seems to be a "neutral" innovative input, since although it increases the probability of having any type of innovation output, it does not affect significantly the relative likelihood among the different innovation output outcomes considered.

In obtaining these results, controls for size, labor skills, exports, group and foreign ownership, among others, are included. The estimation results are presented in Table A.3. The size of the firm has a positive effect on the probability of having an innovative output, particularly with respect to both product and process and only process innovations. On the other hand, unexpectedly, foreign firms do not appear to have different chances of introducing innovations with respect to domestic firms, since the dummy for foreign ownership estimation is not statistically significant in the MNL model estimation. This is also the case for the dummy for being part of a group. On the other hand, labor skills and export activity have a statistically significant impact only on the relative likelihood of both product and process innovations.

Finally, as expected (given the hostile domestic economic environment), the results for the time dummy variable (time01) show that, during 1998–2001, firms are less likely to have a positive innovation output (i.e.

[47] Note that such change does not depend on a particular set of values of the independent variables.

[48] This result holds both for continuous and discontinuous R&D expenditure, although the change in the log likelihood ratio is considerably higher for the former.

to become innovators), since estimated relative likelihood ratios are reduced during this period (except for only process innovations).

4.5. Firm performance

As shown in Table A.3, the fixed effects estimation of Eq. (4) reveals that the dummies for the different types of innovative output have the (positive) expected sign, though high statistical significance is attained for both products and processes (prodproc) and only processes innovators (oproc). An F-test cannot reject the null hypothesis that the impact of these two types of innovation outcomes is equal.[49]

An average impact of the innovation output on labor productivity can be estimated by replacing the three innovation-type dummies by a single innovation output dummy variable inno (i.e. equal to one if innovation output is positive) in Eq. (4). As shown in the last column of Table A.3, the estimated coefficient is 0.132007 and it is significant at the 1% level. This implies that labor productivity is, on average, 14.1% higher innovators than in non-innovators, ceteris paribus.[50] Thus, the overall picture is that being an innovator had a direct benefit for an Argentine manufacturing firm during the last decade: it contributed to improve its labor productivity during the period under analysis.

As expected, the negative sign associated to the time dummy indicates that manufacturing firms attained, ceteris paribus, smaller productivity levels in 1998–2001 than in the previous period. Labor skills are also a significant determinant of productivity. The evidence suggests diminishing marginal productivity of labor, since the estimated elasticity of labor productivity to total employment is slightly less than −0.4. On the other hand, and also unexpectedly, neither being part of a group, investment in capital goods, export activity nor foreign ownership have a positive impact on productivity, once firm-specific fixed effects are included in Eq. (4).[51]

[49] The p-value is 0.5848.

[50] This effect is calculated as $e^{0.132007} - 1$.

[51] In fact, all of these variables have the expected signs and are highly significant if firm-specific fixed effects are replaced by 21 sector-specific dummy variables (not reported).

5. Concluding remarks

In this paper, the innovation activities of Argentine manufacturing firms during 1992–2001 are analyzed, using matched data from two innovation surveys that accounted for a significant share of the industrial activity during the 1990s. Going back to the three questions posed in the introduction, our findings have shown that:

(a) large firms are more prone to engage in innovation activities and to launch innovations to the market. In contrast, foreign ownership does not have any effect on those variables. While labor skills have a positive and significant impact on the probability of undertaking innovation activities, the same does not happen with export activity. On the other hand, labor skills and exports have a statistically significant impact only on the relative likelihood of obtaining both product and process innovations;
(b) performing innovation activities (in house R&D and technology acquisition) enhances the probability of becoming an innovator, but in heterogeneous ways. While technology acquisition does not affect the relative likelihood of the innovation output outcomes, R&D increases the odds of both product and process and only product innovations vis a vis only process innovations;
(c) innovators performed better than non-innovators in terms of labor productivity, during 1992–2001. Innovating, jointly with labor skills, seem to be the main determinants of firms' productivity, since once firm-specific fixed effects are included, neither being part of a group, export activity nor foreign ownership have a positive impact on productivity.

In making these conclusions, it is important to acknowledge that the sample of firms on which we have worked might have performed better than the national average. Under such circumstances, the conclusion that, for example, innovation in products and processes has a positive impact on productivity might be valid for this sub-group of best performing firms, while we do not know what could have happened with those firms that closed during the period under analysis (and were not covered by the innovation surveys).

Some of our findings certainly call for more research, since they are somewhat unexpected (for instance, the lack of influence of foreign ownership on firms' innovation activities and outputs). However, note must be taken that, in the case of our analysis on innovation outputs, foreign ownership, as well as other variables such as size, exports, labor skills, etc., are considered only as control variables, since our focus is on the impact of innovation activities on those outputs. Hence, there is a need to address those issues in new research projects specifically aimed at their analysis.

An important lesson from our findings is that in spite of low R&D expenditures in Argentina's manufacturing industry, firms consider R&D activities as part of their routines and a valuable asset to be preserved even in bad times. Our results show that they do so for good microeconomic reasons, since R&D contributes to becoming an innovator and, hence, to higher productivity levels than competitors which do not innovate.

It is very relevant to take into account that continuous R&D efforts have a considerably larger impact on the probability of having an innovative output (in particular, regarding both product and process innovations) when compared to discontinuous expenditures. Hence, discontinuing in house R&D activities would have a negative influence on the results of those activities. This finding reminds us of the importance of considering that firms also learn to innovate and that this learning must be a continuous process to be effective.

Since knowledge and innovation processes have a strong cumulative nature, it comes as no surprise to find that better results are obtained when firms internalize R&D activities as part of their routines than when they undertake isolated innovation projects. While this finding may not be unexpected when developed countries are analyzed, it is interesting to find that it is also valid for developing countries. Hence, technological policies should aim at fostering firms to maintain permanent innovation departments instead of only subsidizing specific projects—as it is still the case in many countries, such as Argentina for instance.

Appendix A

A.1. Definition of variables

The definitions of the variables used in the econometric regressions are found in the following table (parentheses refer to the names of the variables as they appear in the table of econometric results) (Table A.2).

A.2. Balanced and unbalanced panel data estimation

Table A.4 presents the results of the estimation of a simple model of labor productivity (similar to the model in Eq. (4)), in order to compare results based on the balanced and unbalanced panel data sets. The former is the subset of firms on which our empirical analysis has been made. The latter includes, in addition, firms that were surveyed in only one of the innovation surveys.

To be able to use a firm fixed effect estimator, the variables included in this model should be observed in 2 years (at least). Therefore, since the unbalanced panel includes firms surveyed only in 1992–1996 or 1998–2001, the regressors included in this simple model are those for which we have information in 1992 and 1998, in addition to 1996 and 2001. This explains why its specification is simpler than the model in Eq. (4).

Expectedly, as shown in Table A.4, standard errors are slightly smaller in the unbalanced panel, since sample size is considerably larger than in the balanced data set. As a consequence, statistical significance is usually lower in the latter. Nevertheless, the signs of the estimated coefficients are the same in both data sets, and their magnitudes are very similar in all cases. As stated in Section 3.1, these results provide evidence that, if existent, the possibility of selection bias arising by restricting our analysis to the balanced panel data set is not likely to have an important impact on our conclusions.

Table A.1
Studies based on the CDM approach

Study	Individual data	Endogenous variables	Estimation method	Other comments
Crepon et al. (1998)	France 1986–1990	R&D, patent (or share of innovative sales), labor productivity	ALS	Censored data for R&D
Duguet (2002)	France 1986–1990	Radical innovation, incremental innovation, TFP growth	FIML logit for innov., 2SLS or GMM for TFP growth	Separate estimation for various technological opportunities
Galia and Legros (2002)	France 1994–1996	R&D, innovation output, training, quality, profitability	ALS	Censored data for R&D and training, dichotomous data for quality; allows for feedback effects
Van Leeuwen and Klomp (2001)	Netherlands 1994–1996	Innovation input (R&D or innov. expend), innovation output, productivity (in levels or growth rates)	OLS, 3SLS limited system, or 3SLS full system (with or without correction for selectivity)	Productivity measured by revenue per employee or value added per employee; feedback effect from revenues on innov. output
Van Leeuwen (2002)	Netherlands Panel data from CIS2 and CIS2.5	R&D, innovation output, growth in revenue/employee	FIML gen. tobit for R&D or innovation output; separate FIML for growth of revenue/employee with correction for selection bias	Dynamic model for 1994–1996 or pooled model for 1994–1996 and 1996–1998; innov. output measured by new sales or by new and improved sales
Benavente (in press)	Chile	R&D, patent (or share of innovative sales), labor productivity	ALS	Censored data for R&D
Lööf and Heshmati (2002)	Sweden	Innov. expend. per employee, innovative sales per employee, and value added per employee	FIML for generalized Tobit on innov. expend., other equations by 2SLS with correction for selection bias	Also estimated with only radical innovations; productivity estimated in levels and growth rates; feedback effect from productivity on innov. output
Lööf and Heshmati (in press)	Sweden	Innov. expend. per employee, innovative sales per employee, and labor productivity	FIML for gen. Tobit for innov. input, other equations by 3SLS with correction for selection bias	Labor productivity measured as innov. sales/employee or value added/employee; feedback effect from productivity on innov. output
Lööf et al. (2001)	Finland, Norway and Sweden 1994–1996	Innov. expend./employee, innovative sales/employee, and labor productivity	FIML for gen. Tobit for innov. input, other equations by 2SLS and 3SLS with correction for selection bias	Estimation for all innovations and for radical innovations; feedback effect from productivity on innov. output
Jefferson et al. (in press)	China Panel data 1995–1999	R&D, share of innovative sales, productivity (or profitability)	Separate estimation of each equation by OLS and IV	Square term on innovative sales
Parisi et al. (2002)	Italy, Panel data 1992–1994 and 1997–1995	Labor productivity growth, product innovation, process innovation Product and process innovations estimated by logit or conditional logit, product. growth estimated by IV		

Source: Mairesse and Mohnen (2003).

Table A.2
Definition of variables

Variable	Definition
Time dummy (time01)	Dummy equal to 1 if the observation corresponds to the period 1998–2001 (equal to 0 if the period is 1992–1996)
Innovation activity (dinne)	Dummy equal to 1 if the firm reported positive innovation expenditures during in period *t*
Innovation expenditures (linne)	Yearly average of total expenditure in innovation activities during period *t*, per employee at the end of the period (measured in log)
Innovation outcome (TYPE):	Unordered response variable that indicates the outcome of the innovation process in firm i during period t, classifying it either as a non-innovator (N), both product and process innovator (B), only process innovator (C), or only product innovator (D)
Both product and process innovators (prodproc)	Dummy variable equal to one if the firm introduced new products and processes during period *t*
Only product innovators (oprod)	Dummy variable equal to one if the firm introduced new products (but not processes) during period *t*
Only process innovators (oproc)	Dummy variable equal to one if the firm introduced new processes (but not products) during period *t*
Labor productivity (lprod)	Sales of own products per employee during period *t* (in log)
Size	Total employees in period *t* (in log)
Foreign (FDI10)	Dummy equal to one if foreign capital share is equal or greater than 10%
Skills	Average share professional labor during period *t*
Investment in capital goods (IK)	Binary variable equal to one if the firm reports positive physical capital investments in period *t*
Group	Dummy equal to one if the firm is part of a group in period *t*
Exports (Expo)	Dummy equal to one if the firm exported during period *t*
Continuous R&D (RDc)	Dummy equal to one if the firm reported positive R&D expenditures in every year during period *t*
Discontinuous R&D (RDnc)	Dummy equal to one if the firm reported non-continuous R&D expenditures in period *t*
Technology acquisition (TA)	Dummy equal to one if the firm reported positive Technology acquisition expenditures during in period *t*
SectRN[a]	Dummy equal to one if the firm belongs to the natural resources intensive sector[b]
SectRD[a]	Dummy equal to one if the firm belongs to the R&D intensive sector[b]
SectESC[a]	Dummy equal to one if the firm belongs to the scale intensive sector[b]
SectL[a]	Dummy equal to one if the firm belongs to the labor intensive sector[b]

[a] When the variable is interacted with a time dummy (for example, in Table A.3), its name is preceded by the letter *t*.
[b] This classification was developed by Pavitt (1984) and later adapted by Guerrieri and Milana (1989).

Table A.3
Econometric results

Dependent variable	Innovation activities (Two-part model)		Innovation output (Multinomial Logit[a]) (Type)			Labor productivity (Fixed effects[b])	
	Dinne[c]	Linne[d]	*B*	*D*	*C*	Lprod	Lprod
Size	0.7227496*** (0.2454854)	−0.6523946** (0.2898289)	0.5901086*** (0.0825137)	0.173078 (0.118696)	0.5375049*** (0.1197281)	−0.4145755*** (0.0462069)	−0.4129286*** (0.0461298)
tSize[f]	−0.0599456 (0.1270231)	0.3547184*** (0.130907)					
Group	0.03541 (0.3334664)	−0.2109047 (0.2832935)	0.2035518 (0.22548)	0.266731 (0.31999)	−0.1845303 (0.3254185)	0.0891143 (0.060932)	0.0864796 (0.0607808)
Skills	4.480927**, −1.993.537	−0.4101189, −1.654.719	2.61342*, −1.356.927	1.829.103, −1.779.228	194.976, −17.532	0.6944377* (0.354674)	0.6740537* (0.3535194)
Expo	0.4765549 (0.3177594)	0.0121961 (0.4308908)	0.3526753* (0.182325)	0.4320198 (0.270318)	0.2801319 (0.2743114)	0.0561897 (0.0643553)	0.0533674 (0.0642232)
FDI10	0.53395 (0.4806888)	−0.1193713 (0.3548181)	−0.4358236 (0.2925708)	−0.3530488 (0.41009)	0.0127442 (0.3782065)	0.0938894 (0.0833943)	0.0956493 (0.0833)
tsecL[e]	0.4034907 (0.4829086)	−0.7214097 (0.511376)	−0.1128775 (0.551459)	−0.130942 (0.740022)	−0.7632716 −1.017.219	−0.1664689* (0.0894304)	−0.1658368* (0.0893506)
tsecESC[e]	−0.3113273 (0.4446709)	−0.208615 (0.3839441)	0.0925435 (0.5451837)	0.8177549 (0.731971)	−0.7699289 (0.9875254)	−0.0019162 (0.0840801)	−0.0054537 (0.0839168)
tsecRN[e]	0.9288309** (0.4725697)	−0.3681611 (0.3953274)	−0.1563992 (0.5282745)	−0.3115208 (0.716365)	−1.015.669 (0.9514779)	0.0676435 (0.0826097)	0.0686802 (0.0825213)
time01	0.7620513 (0.6937015)	−0.9559082 (0.7346269)	−2.539374*** (0.4692629)	−1.491689** (0.597407)	−0.4013005 (0.891913)	−0.2134977*** (0.0705413)	−0.2121236*** (0.0698275)
RDc			2.867781*** (0.420588)	2.567582*** (0.477809)	1.027183* (0.5262412)		
RDnc			1.773987*** (0.3813472)	1.799092*** (0.459242)	0.6267478 (0.5136624)		
TA			1.845397*** (0.2344891)	1.424984*** (0.321446)	2.177521*** (0.3189351)		
Prodproc						0.136026** (0.0551411)	
Oproc						0.177665** (0.0813601)	
Oprod						0.0884446 (0.075616)	
Inno							0.132007*** (0.0505087)
IK						0.05614 (0.0542857)	0.0570048 (0.0541877)
Num. of obs.	516	651	1420			1410	1410
Num. of groups	258	457				718	718
Avg. obs. per group	2.0	1,4				2.0	2.0
Log likelihood	−146,05848		−1.146,1246				
Diagnostic tests	LR $\chi^2(10) = 65.55$***	$F(10,184) = 3.63$***	LR $\chi^2(96) = 785.03$***			$F(13,679) = 12.20$***	$F(11,681) = 14.37$***

Standard errors in parenthesis.

[a] ML estimation. Includes 21 sectoral dummies (not reported).
[b] Linear fixed effects estimator.
[c] Conditional fixed effects Logit (ML estimation).
[d] Linear fixed effects estimator.
[e] Interaction with time01.
* Indicate statistical significance at 10%.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

Table A.4
Balanced and unbalanced panel data estimation

Dependent variable	Labor productivity[a]	
	Balanced panel (lprod)	Unbalanced panel (lprod)
Size	−0.3346141*** (0.0277162)	−0.3393368*** (0.0218793)
Skills	0.6892611*** (0.2142989)	0.7852863*** (0.189351)
Expo	0.0425859 (0.035433)	0.0698259** (0.0280968)
time96	0.1865074*** (0.0258829)	0.1493526*** (0.0175704)
time98	0.1950932*** (0.0255788)	0.1722489*** (0.0219574)
time01	−0.0571889** (0.0262228)	−0.072394*** (0.0224403)
Num. of obs.	2786	5683
Num. of groups	718	2204
Avg. obs per group	3.9	2.6
Diagnostic tests	$F(6,2062) = 48.32$***	$F(6,3473) = 83.93$***

Standard errors in parenthesis. *Indicate statistical significance at 10%.
[a] Linear fixed effects estimator.
** Indicate statistical significance at 5%.
*** Indicate statistical significance at 1%.

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