

Innovation and R&D Expenditures in Argentina: Evidence from a firm level survey¹

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Abstract

In this paper we look at the evidence regarding innovation and R&D expenditures of Argentine firms using a recent survey conducted by CEPAL-INDEC. The Schumpeterian tradition suggests that innovation efforts are positively associated with firm size and market share. We find that both variables are significant and positive and this result is robust to different econometric techniques, different sampling, and also survives when we include sector dummies. Foreign capital participation also raises the level of both R&D and total innovation expenditures.

We explore whether different industry characteristics like concentration, tariffs, skill intensity and market size have also any impact on technological decisions taken at the firm level. We found that both concentration and larger tariffs negatively affects incentives to perform R&D activities. Also skill-intensity is positively correlated with innovation activities. With regard to the quantitative impacts of the various variables, we find that industry level determinants have a much larger impact than firm-level indicators.

We evaluate the impact of a public sector program, FONTAR, aiming at fostering R&D activities in the private sector. In order to evaluate the causal relationship we perform a Difference in Difference (DID) estimation. The FONTAR variable does come out positive and significant for R&D expenditures, but we don't find any positive impact for total innovation. The same conclusion comes when we applied Matching Methods to select for each treated firm a matched individual (or group of individuals) within the non-participating firms. We finally combined matching methods and DID when we compare the before and after difference in the R&D and innovation outlays for each treated and matching control observations. The result again suggests that the FONTAR program has had a positive effect on R&D expenditures and none on total innovation.

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1. Introduction.

There is a vast theoretical and empirical literature that has singled out technological innovation as a key source of growth in productivity and in income per capita. From this evidence, comes a strong demand for understanding what are the determinants of technological progress and how countries can foster this process via public policies. In response to these demands there are some recent studies that have empirically investigated the determinants of innovative activities (IA) across countries (Varsakelis (2001), Lederman and Maloney (2003)). There are also efforts to investigate this relationship at the firm level for developed economies (Cohen and Levinthal (1990), Cohen and Levin (1989), Griffith et al (2003)). Still there are very few studies that analyze the determinants of technological progress for developing countries using firm level data².

The purpose of this study is to partially fill this gap looking at the magnitude and determinants of technological innovation made by Argentine firms. We use a recent data set collected by CEPAL and INDEC to quantify the magnitude of innovation expenditures during the 1992-2001 period and we will also provide a micro-econometric analysis of its determinants. In particular, we will estimate the impact of firm size and market share, foreign capital participation, market conditions, trade regime and a public program aiming at fostering R&D investment by the private sector.

The quantitative information shows that technological upgrades are implemented mainly through capital goods purchases and licensing (technology transfers). In a very small proportion (between 5 and 15%) innovation is done through investment in research and development. In terms of firm sales, the level of R&D is very small (around .20%). This value, nevertheless, is in line with other developing economies like Mexico and Chile.

² Among the few available studies we have the paper by Benavente (2002) using data for Chile and Meza-Gonzalez and Mora-Yague (2002) employing a Mexican survey.

We observe an increasing trend in mean R&D for the sample of firms during the nineties. This contrast with the sharp decrease observed since 1998 in other innovation expenditures (i.e. capital good investment and licensing) coinciding with the macroeconomic downturn.

We employ this data set to test some simple hypotheses regarding the determinants of innovation decisions at the firm level. Clear-cut predictions come from the Schumpeterian tradition in which technological efforts are positively associated with firm size and market share. We show that these hypotheses are consistent with the Argentine data. We find that both variables are significant and positive and this result is robust to different econometric techniques, different sampling, and also survives when we include industry characteristics and sector dummies. We also find that foreign capital participation raises the level of both R&D and total innovation expenditures.

We also investigate the effect of different industry level features like concentration, tariffs, skill intensity and market size. We found that concentration at the level of the industry negatively affects incentives to perform R&D activities. This result is robust to the inclusion of industry dummies. Thus more competitive market environments (as oppose to monopoly market structures) are a positive factor fostering innovation by firms. This competition effect seems to be reinforced by the results coming from the tariff variable. We find that firms operating in industry sectors facing lower tariffs, other factors constant, spend more in R&D. This result, nevertheless, does not survive when we introduce sector dummies and there is no effect of tariff on total innovation expenditures. We also find that industries having a larger participation of skilled labor within the total labor force spend more in innovation activities. With regard to the quantitative impacts of the various variables, we find that industry level determinants have a much larger impact than firm-level indicators.

Finally we evaluate the impact of a public sector program, FONTAR, aiming at promoting R&D activities in the private sector. This program was in full operation from 1997 onwards. We find that this variable comes out positive and significant when

included as another regressor, but we suspect that this result can be affected by a selection (endogeneity) bias. Thus, in order to evaluate the causal relationship between these government incentives and firm behavior we perform a Difference in Difference (DID) estimation. In this case, the FONTAR variable does come out positive and significant for R&D expenditures, but we don't find any positive impact for total innovation expenditures. The same conclusion comes when we applied Matching Methods to select for each treated firm a matched individual (or group of individuals) within the non-participating firms. The computed mean difference in R&D expenditures between the treated and the selected control firms comes out significant. We finally combined matching methods and DID when we compare the before and after difference in the R&D and innovation outlays for each treated and matching control observations. The result again suggests that the FONTAR program has had a positive effect on R&D expenditures (and none on total innovation) of around 50 to 70 US\$ per employee.

The rest of the paper is organized as follows. In section 2 we describe the main features of the survey and present some results regarding expenditure decisions and other variables characterizing innovation activities taken by Argentine firms during the 1992-2001. In Section 3 we discuss the main hypothesis that the theoretical literature has raised for explaining firms decisions on technological investment. This discussion serves as a motivation for the empirical analysis we perform in section 4. Section 5 concludes.

2. Innovation activities performed by Argentine firms: some aggregate indicators.

In this section we want to briefly summarize some of the principal findings of the technology study conducted by CEPAL and INDEC³. The information was collected in two surveys. The first covers the 1992-1996 period while the second collects information between 1998 and 2001. Following international practice (see appendix A for the details)

³ The full results of the two surveys (Encuesta Nacional sobre la Conducta Tecnológica de las Empresas Industriales Argentinas) are described in INDEC (1998) and INDEC (2003).

the questionnaire defines innovation activities assuming both an “input” and “output” view. Within the first approach, the questionnaire ask firms to indicate how much resources are spend in the following activities: (i) R&D (internal and external), (ii) purchase of capital goods; (iii) hardware; (iv) software; (v) licensing of a new technology; (vi) industry and engineering design, (vii) new management techniques; (viii) training; (ix) consulting services. The sum of all previous items will be called total expenditures in innovation activities (TEIA), the sum of items (iii) to (iv) is some time referred to as “embodied” technological knowledge, while items (iv) to (ix) constitute “disembodied” technological investments. As we see the survey uses an ample definition of what constitutes innovation. This is important given that, as we will show below, in Argentina (as in most developing countries) innovation efforts are in a very small proportion implemented through narrowly defined R&D.

In terms of output indicators, the survey collects information on patents and also asks firms for the final application of the technological investment. That is, if an innovation activity aims at improving: (i) product; (ii) production process; (iii) organizational/management changes or (iv) commercialization/marketing.

Table 1 reports the behavior of some of the main variables (summing across all firms) including TEIA and other firm level indicators. We observe that innovation expenditures grew almost 58% between 1992 and 1996 reaching a value of 1766 millions of current pesos/dollars in the last year. Between 1998 and 2001, and for the sample of firms integrating the second sample we observe a decline in the absolute value of TEIA. Surely the strong downward movement suffered by the Argentine economy in this period is in part responsible for this dynamics. In terms of percentage of total sales, TEIA is maintained relative constant during both periods suggesting that the financing of IA is related in part to current income. The exposure of the firms of the sample to international trade flows is significant both from the export and import side. Regarding export performance, we observe an increase in the export share between the extreme years in both samples. On the other hand, import penetration rose between 1992 and 1996 and declined between 1998 and 2001.

Insert Table 1

Table 2 describes the composition of expenditures in innovation activities across major categories for selected years. The main source of technology innovation is the purchase of capital goods. For example, in 1996, a total amount of 977 millions of pesos/dollars of capital good investment was associated with the introduction of new goods and/or new productive processes (2.35% of firm sales). This represents 58% of the TEIA done by the firms in the sample in that year and also it was equivalent to 45% of total capital good investment realized by these establishments (not shown in the table). Thus, this evidence suggests that indeed capital good purchases are associated in a large proportion with technological upgrades. A second mayor expenditure category in IA is the purchase of licenses representing 201 millions pesos/dollars in 1996 (12 % of the TEIA and 0.34% of firm sales). R&D, which comprises the more narrow definition of IA, comes in second place in 2001, third place in 1992 and 1998, while it is fifth in 1996. For year 2001 expenditures in R&D reached 110 millions (0.26% of total firm sales) gaining a significant share within TEIA (17%). The amount spent in 2001 on this IA item is significantly larger compared to previous years. This evidence suggests that firms have substituted purchases of foreign technology via licensing (and may be capital goods) by engaging more actively in R&D activities.

Insert Table 2

A final remark regarding the innovation performance of firms in Argentina refers to the number of patens obtained. For the 1992-1996 period, out of 1533 firms, 90 reported they had obtained at least one patent (413 in total). For the 1998-2001 period, 98 enterprises declared they had done some patent activity, being the total amount of patents equal to 317.

3. Conceptual framework.

What determines the decision of a firm to engage in innovation activities? In this section we provide a very simple conceptual framework to understand this decision problem in order to motivate the empirical exercise we perform in section 4. In discussing the theoretical arguments behind innovation efforts we will distinguish between those determinants identified at the firm level and those that vary across industries. The first approach has been associated with the Schumpeter tradition while industry characteristics have been suggested by the more recent literature.

3.1 Firm level determinants: size and market share.

Most of the empirical analyses that have used firm level data have concentrated in testing the so called Schumpeterian tradition (Schumpeter (1942)). This can be resumed in two hypotheses (Cohen and Levin (1989): (i) innovation increases with firm size; (ii) innovation increases with market concentration.

Several arguments have been advanced to justify the positive relationship between innovation activity and size. One is that, in presence of imperfect capital markets, large firms are better equipped to provide collateral (more stable and larger flow of sales) to secure financing for otherwise very risky R&D investment. A second argument is that there are economies of scale in technological innovation activities, thus returns to innovation rises with the size of production to which the innovation is going to be applied. A related argument is that in the presence of large fixed cost produced by technological development, R&D returns increase when these cost spread over a larger amount of sales.

The justification for a positive association between innovation efforts and concentration has been framed in terms of “ex-post” and “ex-ante” market power (Cohen and Levin (1989)). By ex-post market power it is understood the Schumpeterian idea that firms incentives to invent are driven by expectations of *future* market power which will justify the current investment in R&D. This is the principle behind the justification of patent laws. Notice that this expectation of ex-post market power need not be related to current

level of market concentration. Actually, some models have suggested that the ex-post market power hypothesis has an implication for a positive association between innovation and market competition. This is because at the margin an innovation can produce larger gains (in market shares and profits) in an already very competitive environment (see Arrow (1962)). We can extend this reasoning for an open economy context. As trade liberalization and exposure to foreign markets make the domestic market more competitive, we could expect that this will increase firm's incentives to pursue innovation.

On the other hand, ex-ante market power implies that firms that currently enjoy monopolistic power will have greater incentives to engage in technological initiatives given the reduced uncertainty regarding rival firm behavior, which in turn makes future sales more predictable and stable. In addition, the above-normal profits would provide the financing for R&D expenditures in case of distortions in financial markets.

Thus theory provides a rather ambiguous prediction regarding current market power and innovation. The positive association coming from ex-ante concentration could collide with incentives coming from ex-post gains in market power, which are larger when the market is already very competitive.

3.2 Industry characteristics.

More recent research has emphasized that an important part of the variability in R&D across firms is actually explained by across industry variability. This was shown by the important explanatory power that industry dummies have when included in the regressions and how the inclusion of these variables reduced the statistical significance of other firm level indicators like market share. Hence, research efforts were directed to try to identify the industry characteristics that are most relevant. The resulting debate can be summarized in terms of three factors: industry demand ("demand pull"), industry

technology opportunities (“technology-push”) and appropriability conditions (Cohen and Levin (1989)).

Demand factors, represented by the size of the market or its rate of growth, would affect incentives to invest in R&D because the cost of R&D required to improve a production process or introduce a new product is in general independent of the level of output once the innovation is made. Thus a large market (or the greater its expected rate of growth) would make the benefits of innovation more significant. Thus, other factors constant, industries facing greater and more dynamic demand would invest greater resources in technology.

Technology opportunities refer to the fact that certain industries face lower cost of innovation compared to others. This in turn could be explained by differences in the exogenous (from the point of view of the industry) developments in the underlying technological knowledge used in each sector. Also, we could think that industries that use more intensively skilled labor are better equipped to perform innovation activities. In practice the evaluation of the impact of this opportunity factor (or technology push indicator) has been done using industry dummies for specific sectors (chemical, electrical, mechanical), indicators of factor intensities, or closeness of industries to science or the sources of extra-industry knowledge (Cohen and Levinthal (1988)).

Finally, an important factor affecting firms’ incentives to invest in innovation is the degree of appropriability, meaning to what extent technological developments that imply new production processes or new product quality cannot be copied or imitated at low cost. Of course the recognition that this could be a serious problem undermining incentives to technology development is what has pushed patent legislation. Still it has been shown (Mansfield (1986)) that industries differ in terms of how valuable are patents in effectively protecting from copying and imitations. Only in the pharmaceutical and chemical sectors patents emerge as an effective instrument. In other industries, investment in complementary assets such as marketing and customer services can

facilitate appropriation when neither strong patents nor technical barriers to imitation are present (Cohen and Levin (1989)).

In summary, we recognize that market demand behavior, technology opportunities and appropriability conditions vary across industry sectors, which in turn would tend to affect incentives of individual firms to do R&D investments. Now, as it will be clear in the next section, in many cases we will not be able to find good proxies for these variables. Still, the above discussion suggests that some type of control, at least industry dummies, have to be incorporated if want to avoid biased results.

4. Empirical analysis.

In this section we present the results we obtain from the regression analysis in which we try to empirically identify the impact of various factors on firm's innovation expenditures. Before describing the results of the estimations we briefly describe the data set we use and the definition of the variables.

4.1 Definition of variables, description of the data set and the main stylized facts on R&D and innovation expenditures by firm.

To perform the statistical analysis we have constructed a panel linking the two surveys which main features were summarized in section 2. We have annual data on innovation expenditures by firm for years 1992, 1996 and 1998-2001. The coverage of some of the firm's characteristics (employment, sales) was limited so we completed this information using the annual industry survey.

Table 3 presents, for each year, the sample size, the mean value of R&D expenditures (in terms of total sales and by employee) and the proportion of firms that report zero R&D expenditures. We see that a large proportion of firms (around 72%) do not engage in any R&D activity. More important and somewhat surprising, there is a clear upward trend in R&D expenditures measured both relative to firm's total employment and to gross

income (sales). In Table 4 we describe the same information for total innovation expenditures (TEIA). Now we see that a larger amount of firms reports some level of innovation outlays (around 50% at the end of the period). Still, and contrastingly with what we observed for R&D, there is a clear decreasing trend that sets in since 1998 coinciding with the macroeconomic downturn suffered by the economy.

Insert Table 3 and 4

In most of the statistical exercises we present below, we use as our variables of interest R&D and total innovation expenditures per employee⁴. We choose to work with both indicators (instead of using TEIA alone which incorporate R&D as well) because, as we already showed, the dynamics of the two variables are quite different along the period of analysis. Moreover, some of the hypotheses described previously seem more appropriate for R&D as compared to TEIA. This is clear for the idea that R&D is subject to economies of scale or that it implies large fixed costs. This is less justifiable for the case of technology licensing, or firm expenditures in software and training⁵. Second, and perhaps more important, we want to compare our results with others estimations applied to developed and developing countries. Many of these studies work only with the R&D indicator⁶.

It could be interesting to know whether there is an important variation across industry sectors in terms of innovation efforts. As already, indicated in section 3 there is an important literature that has emphasized that the most significant determinants of innovation vary at the industry level. We would like to see, for example, whether the above increasing trend in R&D is driven by those sectors that are already R&D-intensive or whether this increase is occurring across all industries.

⁴ We have also run all the statistical exercises using R&D and TEIA in terms of sales with no significant changes in the results we present below.

⁵ Though it could be applicable for capital purchases.

⁶ See the paper by Benavente (2002) for Chile and Crepon et al (1998) for France.

Table 5 presents information that helps to address the above issues. For selected years we show R&D and TEIA expenditures per employee. We can easily identify which are the sectors that are innovation-intensive. For example, in year 1998, Chemicals, Plastics, Petroleum distillery, Paper, Non Metal Mineral, Audio, TV and communication and Motor Vehicles were the industries that show the largest values for TEIA. This ranking is not necessary the same when we consider R&D. Chemicals does belong to the group of top sectors, but we have also other industries that were not important in terms of the TEIA/sales ratios, like Computer Equipment and Medical Apparatus. Regarding the dynamic behavior of these indicators we see that comparing 2001 and 1992 we observe that almost all sectors raised their level of expenditures in R&D while the inverse is observe for total innovation outlays (with the exception of petroleum distilleries). Figure 1 shows that the increase in R&D expenditures were more significant (in % points) in sectors that were originally less R&D-intensive. Thus, a sort of “convergence” has taken place.

Insert Table 5

Insert Figure 1

How the decision on R&D expenditure varies with the size of firms? A first assessment of this issue could be obtained from the information presented in Figure 2, which describes the behavior of some R&D indicators across the size distribution of firms. We see that the first quartile (25% largest firms in term of total employment) concentrate a large proportion (76%) of total R&D outlays. Still in terms of expenditure by employee, the differences are not that significant. It is true that expenditures rise with size up to the third quartile. But from this point onwards it remains relative stable (at around 35 \$ per employee). This suggests a non linear, concave relationship between innovation expenditures and size which is consistent with the view that R&D is subject to important economies of scale. We will investigate this nonlinear relationship more formally in the regression analysis.

Insert Figure 2

Another interesting inquire that we could make is how innovation expenditures vary with the structure of ownership of the firm. That is, whether participation of foreign capital is associated with larger levels of R&D. As we will emphasize below this could be an important channel that could facilitate innovation. This information is presented in Figure 3. It is shown that effectively larger participation of external capital is associated with higher innovation expenditures both in R&D and in other innovation activities. In this regard outlays per employees are significantly larger for firms with a foreign capital participation of 75% or higher compared to those with zero or lower than 25%. These are the two quartiles where most of the observations are clustered.

Insert Figure 3

Are R&D expenditures associated with specific industry sectors? We already presented in Table 3 some industry level information. Below in Table 6 we describe for each segment of the size distribution of firms (for year 2001), the 2-digit ISIC activity corresponding to the top ten firms (in terms of R&D/employee ratio). We have highlighted those sectors that appear more frequently. Thus we learn that firms belonging to the chemical industry (sector 24) are among those that spend more on R&D per employee. Moreover, we observe that this behavior does not depend on the size of the firm as we found this type of establishment in all segments of the distribution. Another sector that contains an important concentration of firms with large levels of R&D per employee is Machinery and Equipment (sector 29). Still in this case it seems that most of these firms are relatively large in size (most of them are located in the 2 quartile, between 96 and 222 employees). Finally another sector for which we encounter a large proportion of firms within the top 10 R&D investors is Food and Beverages (sector 15). Similarly with Chemicals, they are located along the whole size distribution. This evidence suggest that in some cases large values of R&D expenditures at the firm level can be associated with a particular sector, though this is far from being a general rule.

Insert Table 6

4.2 Econometric results: pooled regressions.

As suggested by the theoretical analysis summarized in section 3 the decision to invest in technology is affected by variables defined at the firm level and also by industry characteristics. Within the first set of variables we will evaluate the effect of size and market power. Another firm level indicator that in the case of developing country studies could be very important is the participation of foreign capital in the ownership structure of the firm. This could mean that the local firm is associated with a foreign multinational which could facilitate innovation both by providing technical assistance and financing.

Regarding industry characteristics we will use as a technology opportunity factor an indicator of skilled labor intensity calculated at the industry level (4 digit ISIC). This variable is measured as the share of workers with technical or higher degree within total employment. As a proxy of “demand pull” determinant we will employ an indicator market size calculated as the total sales (gross production) at the industry level (4 digit ISIC). Finally, the competition conditions in each industry will be captured by two variables: the level of external tariffs and an indicator of concentration, both measured at 4 digit of ISIC. Finally we will evaluate the impact of a public program aimed at fostering R&D expenditures of firms called FONTAR.

As we saw above, a key characteristic of our data set is that the dependent variable takes a zero value for many observations reflecting the case of firms that do not engage in R&D activities. Not considering these observations will of course bias our results so we include all of them in the statistical analysis. Still an OLS estimation will in general provide a poor fit given the significant non-linear behavior introduced by this feature. Thus, we run Probit and Tobit estimations⁷.

⁷ The presence of zeros also explains why we don't apply a log transformation to the dependent variable.

Table 7 describes the summary statistic for the explanatory variables. The mean level of employment by firm is 212. Market share is defined as firm sales over production value at the corresponding 4-digit ISIC sector. It has a mean value of 0.033. Concentration is in turn defined as the sum of production of the largest 4 firms over total sales in each 4-digit ISIC industry. Its mean value is .72, reflecting the rather concentrated structure of industry in Argentina. Tariffs are a simple average of 6-digit tariff within each 4-digit ISIC (it includes tariff equivalent of specific duties). We find an important variability for this indicator: the mean value is 17%, going from 0 to a maximum of 35%, which is the level Argentina has consolidated at the multilateral negotiations. Finally we include a variable called FONTAR which is a National Program aimed at financing (on very soft terms) R&D investment. This variable takes the value of 1 if the firm is included in the program. The subsidies started to be implemented in 1996 and were fully implemented since 1998 onwards⁸.

Insert Table 7

In Table 8 and 9 we present the results of the Probit and Tobit estimation for R&D expenditures pooling observations across time and firms⁹. Columns 1 and 2 test the original “Schumpeterian” hypothesis that associates R&D expenditures with firm size and market power. In these specifications we also add the foreign capital participation indicator as this variable also varies at the firm level. In columns 3 and 4 we add industry characteristics defined, as indicated, at 4-digit ISIC. Finally in columns 5 and 6 we introduce the public policy variable FONTAR. We add year effects in all regressions and we show how the results change when we include 2-digit industry dummies. The inclusion of these dummies aim at capturing any other industry characteristic not controlled for by our 4-digit indicators.

⁸ More details on the working of FONTAR will be presented in the next section.

⁹ We have also run regressions using a balanced panel, that is, including those time series observations for firms that appear in all years. The results do not change in any significant way from those we present here.

In the Probit estimations the dependent variable takes the value of 1 if we observe for a given firm in a given year a positive realization for R&D expenditures. Thus these estimations capture the extensive margin (to participate or not) regarding innovation investments while the Tobit specification identifies also the intensive margin (variation in the quantity expended). The tables report the marginal effects so we can assess the magnitude of the partial effect of changes of each explanatory variable.

As we see the simple Schumpeterian model where R&D is correlated with firm size and market share performs quite well. The two variables are positive and significant in most of the regressions. The negative and significant coefficient for employee square confirm that the relationship between size and R&D investment is non linear. The above results are robust to the inclusion of industry characteristics and 2-digit industry dummies. This is specially the case when we consider both the intensive and extensive margins in R&D expenditures (Tobit). Using the estimated marginal effects from this last regression we can calculate the quantitative impact of, say, a 10% change in the explanatory variables. These calculations are described in Table 10. In the case of firm size (employment) the expected R&D per employee rises \$1.14, which is around 4% of the sample mean value (28 \$). This positive effect of size on R&D decisions is maintained up to a plant size of about 2945 employees. On the other hand, the estimated impact of market share is much lower, a 10% increase in this variable (above the mean value of 0.033) raises R&D expenditures per employee in about 0.15 \$.

With regard to foreign capital participation, we also obtain positive and significant coefficient (column 1 of table 8 and 9). Though this partial correlation is maintained when we introduce industry characteristics, it doesn't survive when we include two digit industry dummies. This phenomenon is observed both for the probit and tobit estimations. This suggests that that foreign participation is especially important in certain sectors or that we don't find much variability in this variable within two sector industries. The quantitative impact of this variable (for the regression presented in column 5 of table 9) is also small: a 10% increase foreign capital participation (above the 14% mean value)

raises R&D outlays in 0.19\$ per employee. As we will see below the impact of this variable is much more important when we consider total innovation expenditures.

Within the industry level variables, concentration does not seem to be a significant determinant of the decision to participate or not in R&D activities (probit), but it is when the intensive margin is also considered (tobit). In this latter case concentration is negative and significant in all regressions even in those where we introduce 2-digit ISIC industry dummies. The quantitative impact of this variable is much higher than some of the previous firm-level variables: an increase of 10% in concentration is associated with a reduction of about 1.50\$ in R&D. Tariffs are also negative and significantly related with R&D efforts. Still this negative association is lost when we introduce 2 digit industry dummies. This need not imply that tariff is not a relevant factor in R&D decisions. It just suggests that there is not much variation in import taxes across 4-digit industries within each 2 digit sector. Taking into account the estimated marginal effects (using the regression in column 5) we obtain that a 10% raise in tariff (above the 17% mean value) reduces R&D expenditures in 1.62\$. Again we observe a much stronger response compared to firm-level variables. Thus, the evidence seems to suggest that a less competitive environment, given by either industry concentration or less competition from abroad is associated with lower R&D efforts.

With respect to skills and market size we find that both variables have a positive and significant impact on R&D expenditures in the probit estimations, though the latter variable lost statistical significance in the tobit regressions. Thus technology opportunities given by the average industry skill intensity seems to be a relevant factor facilitating innovation activities. The same is true for market size (though in this case is not relevant for explaining variation in quantity expended). The estimated impact of the skill indicator is comparatively larger with respect to the previous determinants: a 10% increase increases R&D per employee in 1.61\$.

Finally we want to comment on the strongly positive and significant coefficient we find for the FONTAR variable. Here the estimated impact is around 62\$ per employee (that is

more than twice the sample mean). This implies that government incentives have had a significant impact in fostering private sector decisions to undertake risky R&D investments. We postpone to the next subsection a final conclusion on this issue when we apply a DIF in DIF and a Matching methodology to evaluate the causal effect of this policy. Here we only say that the above estimation as well as those presented below can be subject to an endogeneity bias. That is, firms that for other reasons have decided to invest in R&D, would at the same time apply for the government program.

Insert Table 8, 9 and 10

So far we have commented the estimation results for R&D expenditures. Still as we indicated in section 2 this category of innovation is a relative small portion of technology upgrade activities taken by firms in Argentina. Thus we would like to run the same analysis for total innovation expenditures. Table 11 and 12 present the results while table 13 show the estimated quantitative impact. As we see there is not major difference with the previous estimations. All the variables defined at the firm level have the expected sign and are statistically significant, including foreign capital participation that now is significant in all regressions even in those that include two digit industry dummies. Regarding the industry level determinants we also obtain similar results as before with the only difference that now average tariff is not significant in the tobit specification. Thus, it seems that for total innovation outlays the degree of external protection is not a relevant factor to explain variability in the quantity of resources allocated to innovation across firms. Regarding the estimated quantitative impact, Table 13 shows that, as with R&D, industry level determinants have a larger impact on innovation outlays compared to those that change across firms. On the other hand, the estimated impact of the FONTAR program seems also quite large (323\$ per employee). This means that, other factor constant, participating firms spend on average 100% more than the sample average. We will investigate the robustness of this result in the next section.

Insert Tables 11, 12 and 13

A very important issue that we didn't address so far is that of the potential endogeneity of the right hand variables (in addition to FONTAR). May be this is less of a problem for the variables that are defined at the industry level but not for those that vary across firms. In particular, there are strong reasons to believe that firm size and market structure (market share) are simultaneously determined together with R&D expenditures. In the theoretical discussion of section 2 we have emphasized the causality channel going from size and market power to innovation expenditures, but of course causality could run in the other way around. If a firm implements a successful innovation it is most likely that it will gain market share and also expands production and employment (size). We don't have a good strategy to solve this potentially important problem. At this point we can only say that we are not using as dependent variable innovation outcomes per se but innovation inputs (expenditures). For this latter variable the problem of inverse causation should be less significant as in our sample we have a lot of firms that do not engage in R&D expenditures at all and even within those that report positive outlays, there are many that didn't obtain a successful innovation. As an imperfect substitute for a full analysis of this problem we have re-run all of our regressions lagging the explanatory variables one period. In appendix A we present the results for both R&D and Innovation outlays. We do not find any significant change in the results just described.

4.3 Evaluating the impact of public policies on innovation expenditures: controlling for the self-selection bias.

The strong and positive effect that FONTAR has on R&D and innovation decisions is suspected to be affected by an endogeneity bias coming from the fact that firms decide simultaneously whether to participate in the program and how much to spend in R&D. Thus we are not in presence of an exogenous, government-decided public policy that is randomly applied to a set of firms. In other words, the sample of "treated" cross-section observations is not exogenous so the estimations in section 4.2 can be subject to a strong selection bias. In order to solve this problem we propose two methods that are commonly

employed to evaluate causal relationships using non-experimental data. These are Difference in Difference estimation and Matching Methods¹⁰.

But before getting into the details of the estimation techniques it could be convenient to describe in more detail the working of the FONTAR program. In particular we want to describe the type of incentives it provided to private sector firms. During the first two years of its application (1996-1997) FONTAR offered soft credits to private enterprises that were engaged in innovation. These credits could cover up to 80% of the total cost of the project and they pay an interest rate equivalent to 50% of the market rate. For the case of small firms the credit was free from interest rate payments. The most important requirement was to observe the financial guarantees of Banco Nación, which was the public bank in charge of its operation. Since 1997 the program also included the possibility that firms could obtain tax reductions or fiscal subsidies applied to income taxes. This could represent up to 50% of the total cost of the project. In 1999 a new line of funds was added consisting in a direct subsidy to medium and small firms. These funds were not returnable and could not be larger than 50% of the cost of the project up to an amount of 20000 (U\$S) per firm¹¹.

In summary the public incentives for innovation activities included three types of instruments: soft credits, tax deductions and direct subsidies. As indicated in Carrullo et al (2003) during 1995-01, most of the public funds were distributed through tax deductions (around 58 millions dollars, 50% of all public funds). In second place came soft credit lines (33 millions dollars, 28% of the funds) while the remaining 22% were direct subsidies for small firms (25 millions).

There is a growing literature that has aimed at evaluating the impact of public subsidies on R&D expenditures at the firm level. Potentially, these policies could affect private R&D decisions in various ways. It could make firms to spend more of their own

¹⁰ Jaffe (2002) presents a detailed discussion of the alternative methodologies to deal with the selection problem in the evaluation of public research support programs.

¹¹ There were two modalities to implement these subsidies: one for individual enterprises and another for projects involving groups of firms (Programa de Consejería Tecnológicas). For more details see Carrullo et al (2003).

resources on R&D (“additionality” effect) so total R&D expenditures rises above the amount of available public funds. Alternatively, there could be no additional private funds involved as a consequence of the program. On the other extreme, there could be a crowding out effect, through which the presence of public fund make the firms to spend less of their own resources. Wallsten (2000) studies a US program on small, high-tech firms and finds that the SBIR grants crowded-out private R&D one-to-one. Czarnitzki et al (2002) studies the effect of these subsidies in the service sector in Germany and find a strong additionality effect. The evidence of Busom (2000) for Spain is mixed (30% of firms reduced expenditure while the rest increased it. Douguet (2003) finds no crowding-out effect in the case of France but no additionally effect. Lach (2002) finds, in the case of Israel, a strong stimulating impact for small firms but not for large enterprises. Finally, Benavente (2003) found evidence of a strong additionality in the case of Chile.

We cannot implement this type of analysis for the case of Argentina as we don’t have the data on the amount of funds that were granted to each firm nor which of the alternative schemes (credit, tax deductions or subsidies) were used. We only know if a firm participated or not in the program. Thus the question we would like to answer is whether this participation changed the behavior of the firm in terms of R&D expenditures compared to the case in which the same firm did not participate.

It is clear that in general the data to evaluate the above question is not available. Typically what is available is how much the firms that participated in the program have spent on R&D and the same for firms that did not participate. The counterfactual of how much subsidized firms would have spent if they were not in the program is missing. The key issue is to know under what circumstances we can use the information of not participating firms to construct this missing counterfactual. Difference in Difference (DID) estimation and Matching Methods provide two alternative methods to do this.

a. Difference in Difference estimation¹²

¹² This subsection is based on Lach (2002).

Lets focus on the event of a firm receiving a subsidy on company-financed R&D expenditures. Let D_i represent the event of a firm i participating in the public subsidy program and denote y_i the amount of company-financed R&D. Let y_i^1 and y_i^0 be the level of R&D outlays when the firm participated and did not participate respectively. Note that for a given i we either observe y_i^1 or y_i^0 but not both variables at the same time. The gain in company financed R&D expenditures from participating is $\Delta_i = y_i^1 - y_i^0$. We would like to know Δ_i for each subsidized firm. This is the counterfactual outcome associated with the policy intervention. Of course as we mention earlier this counterfactual is missing, as y_i^0 is not observable for the subsidized firms.

We can, however, define an average effect and attempt to estimate its component. Let $E(y_i^1 / D_i=1)$ be the average or expected R&D outlays among firms that received a subsidy. Similarly, let $E(y_i^0 / D_i=1)$ be the expected R&D outlays that would have been incurred by these firms had they not participate in the scheme. Then,

$$\alpha = E(y_i^1 / D_i=1) - E(y_i^0 / D_i=1) = E(\Delta_i / D_i=1) \quad (1)$$

The parameter α measures the average change in company-financed R&D expenditures between what was actually observed among firms that are included in the program and what these firms would have spent had not been enrolled. This is the so-called effect of treatment on the treated. Notice that we aim at measuring just how much private funds are committed to R&D increase as a consequence of program participation (not the exact relationship between public and private R&D funds).

The estimation of this average effect suffers from the same missing counterfactual problem as in the case of the individual firm; we don't observe $E(y_i^0 / D_i=1)$. To solve this problem let start with the most simple and naïve estimator of α based on using the mean expenditures of the non-participating firms. That is, we are going to use $E(y_i^0 / D_i=0)$ as an estimator of the counterfactual $E(y_i^0 / D_i=1)$.

Then define, $\alpha^D = E(y_i^1 / D_i=1) - E(y_i^0 / D_i=1)$ and let estimate α^D by the difference in the sample mean taken over the two groups of firms defined by the support status:

$\alpha^D = y_1 - y_0$. The key question is whether α^D is unbiased estimator of α . To see this let compute the expected value of α^D ,

$$E(\alpha^D) = E(y_1) - E(y_0) = E(y_i^1 / D_i=1) - E(y_i^0 / D_i=0) \quad (2)$$

Summing and detracting $E(y_i^0 / D_i=1)$,

$$E(\alpha^D) = E(y_i^1 / D_i=1) - E(y_i^0 / D_i=1) + E(y_i^0 / D_i=1) - E(y_i^0 / D_i=0) \quad (3)$$

$$E(\alpha^D) = \alpha + E(y_i^0 / D_i=1) - E(y_i^0 / D_i=0) \quad (4)$$

Thus we learn that the simple difference by participating status identifies α plus a potentially non-zero term reflecting differences in R&D outlays between participating and non participating firms in the absence of the policy intervention. Thus this term equals zero if there are no systematic difference in potential R&D between participating and non participating firms, that is, if y_i^0 is mean independent of D_i : $E(y_i^0 / D_i=1) = E(y_i^0 / D_i=0)$. If participation in the program is randomly assigned this condition will hold by definition and the above bias disappears. Clearly this was not the case for the Argentine FONTAR program. As we indicated any firm was free to choose whether or not to enroll and ask for public funds.

Thus in practice participating firms may share some common characteristics that makes them to spend more on R&D. These firms could have different size; they may have some market power; they might belong to a particular industry, etc. Thus, in general, the difference in mean R&D by support status is not only capturing the causal effect of the policy intervention but also part of the effect of excluded determinants of R&D and D.

Of course we could try to control by these excluded determinants so that to eliminate all the differences in potential R&D expenditures among participating and non-participating

firms. In this case the missing counterfactual can be consistently estimated by the mean R&D expenditures of the non-participating firms. This is the selection on observables assumption. This is the way we have attempted to estimate the effect of the FONTAR program in section 4.2 . The FONTAR dummy is capturing the difference in the mean value of R&D expenditures by employee between participating and non-participating firms once we control for observable firm characteristics. Still in general this method will not be satisfactory if we don't have the data for the relevant covariates. There will be unobservable characteristics that cannot be controlled for which will bias the results of the estimation (for example, unobservable managerial skills).

In order to solve this identification problem which is typical of non-experimental data, we will use a fixed effect estimator so that to control for unobservable characteristics of firms. We proposed the following linear specification,

$$y_{it} = x_{it}\beta + \alpha D_{it} + \phi_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where y_{it} is company-financed R&D, x_{it} are observable firms characteristics, ϕ_i is a fixed effect at the firm level and λ_t is a period fixed affect. It can be shown (see Lach (2002) that in this case the estimated coefficient for α correspond to treatment on the treated effect. In addition when equation (5) is estimated using panel methods (in first differences) the estimated coefficient α has a difference in difference interpretation: the expected difference between the growth rates of R&D expenditures between participating and non-participated firms. The “same-firm” differences (to obtain rate of growth) eliminates potential bias from the unobservable firm level characteristics so that the “same-period” difference in rate of growth in R&D captures the treatment effect on the treated.

We implement the estimation of equation (5) using a balanced panel sample composed of 638 firms for a 6 year-period (92, 96 and 98-01). Table 14 presents the results. We show the estimated coefficient for R&D and total innovation expenditures. Also we assess the

impact of FONTAR alone and conditional on explanatory variables that vary at the level of the firm and at the level of the industry.

The results of the estimations suggest that controlling for non-observable factors, the government program has had a positive and significant effect on R&D expenditures per employee. This result is maintained when we include other explanatory variables in the regression¹³. The estimated impact of FONTAR is around 36\$ per employee. This is much lower compared to the simple regression analysis we presented in the previous section, suggesting that this estimates were partially affected by selection bias.

Insert Table 14

Somewhat surprisingly we do not find any causal effect of the government program on total innovation expenditures. As we see the FONTAR coefficient comes out not significant in any of the regressions. Thus, it seems that the government scheme was not effective in promoting other innovation activities besides R&D. We will check the robustness of this result in the next subsection when applying matching methods. But before that, we would like to indicate the potential shortcomings of the DID estimator we just estimated. The most obvious problem is that we are controlling only for time-invariant unobservables. There could be unobserved temporary individual-specific components that also influence participation decisions. For example, firms may decide to enter when they have unusually good projects (Jaffe (2002)). If this cannot be controlled for it may upward bias the impact of the program.

A second potential problem is a bias that may come because of impact of treatment on the treated may not be homogenous across firms. This impact could be different depending on certain characteristics of the potential applicant. As indicated in Heckman et al (1998) in this circumstance DID estimators could be subject to bias because there are some firms

¹³ The somewhat odd results we get for size and size square in the regression (the inverse signs compared to the previous section) have to be interpreted with caution. We have only six time observation for each individual firm. This gives too little within firm variability to precisely estimate the impact of any covariate.

that have participated in FONTAR but at the same time we have no comparable firm (in terms of the vector of observable characteristics X) within the control group that has not participated. The matching methods described next can help to eliminate this type of bias.

b. Matching Methods.

This method is also a way of constructing the counterfactual $E(y_i^0 / D_i=1)$ using the sample of observation of no participating firms. The intuition of the methods is very simple and intuitive. If we assume that all relevant differences between the treated and non-treated groups of firms are captured by the covariates X then we have that,

$$E(y_i^0 / D_i=1, X) = E(y_i^0 / D_i=0, X) \quad (6)$$

Then in this case we know we can use the non-participating firms as a control group, holding X fixed. Then the method is basically to select for each participating (treated) firm a group of “comparable” non participating (non-treated) firms coming from the control group and then associate the difference in R&D expenditure between the treated and non treated as the effect of the R&D public program.

To select the set of these matched firms we need that the distribution of observables is as similar as possible to the distribution of the participating firm. This is done through the estimation of the “propensity score” function, which essentially estimates the probability of participation conditional on X using the sample of participating and non-participating firms. We use the estimated probability of participating to match each treated firm with a non-treated company. This is done by choosing the firm within the control group (non participating) with an estimated probability, which is closest to that corresponding to treated firm i . We do this for all firms in the treated group. Then the estimated average effect of the public program is obtained by calculating,

$$\alpha = (1/n^1) \sum (y_i - y_{j_i}) \quad (7)$$

where n^1 is the number of treated firms in the sample, y_i is the amount of R&D expenditure by employee by firm i and y_j is the level of expenditure of the matched firm in the sample of non treated control group. In general a common support condition is imposed on the treated units. In this case participating firms whose estimated probability is larger than the largest estimated in the non-treated group are left unmatched.

The above method is called the nearest-neighbor matching. Alternatively it can be used a radius matching methods where each treated firm is compared with the average of controls firms within a pre-specified distance or radio in terms of the estimated pscore probability. A third alternative is Kernel Matching where each treated firms is compared with all the j firms in the non-treated group, but the estimated difference is weighted according to their distance from i .

In the matching estimation we will perform below we will show the results applying all the three alternatives. We will estimate the propensity score function over a balanced panel of firms comprising years 1996, 1998 and 2001. This decision is based upon the known fact that this methodology critically hinges on a good selection on observables. Hence, we have to restrict the sample for those years where we have the largest amount of firm level characteristics. Another important clarification with respect to the data is that, as the program was in full operation since 1997 onwards, we have no positive observation for FONTAR for year 1996, while we have 66 participating firms in 1998 and 2001.

Table 15 presents the results of the estimation of the propensity score, which, as indicated, is a probit regression that estimates the probability of participating in the program. We use as explanatory variables size (total employment), market share, foreign capital participation, share of engineers within total employment, share of skilled worker (including workers with technical or higher degree), and export and imports over production. We see that size, foreign capital participation and the skill variable are significantly different from zero. Still while larger size and more skilled labor forced is

positively associated with the probability of participation, the inverse occurs with foreign capital participation.

Table 16 shows the estimated value for mean difference in R&D expenditure per employee between the treated group and matched controls for the three alternative matching methods. As we see the difference is positive and significant for R&D expenditures but it is not for total innovation. The results are somewhat weaker for the Kernel matching method though here the standard errors have to be bootstrapped so results vary with the number of iterations. The estimated impact of FONTAR is above 50\$ per employee which is somewhat higher than that obtained in DID. On the other hand, the result with the matching method confirms what we have already obtained using the DID in the sense that we find causal effects of FONTAR on firm R&D expenditures, but none in the case of total innovation expenditures.

The matching estimation improves upon DID in the dimension of using comparable set of treated and control firms. Still, it is subject to the important drawback that we are selecting on observables. In the absence of good data describing these characteristics the estimation may be subject to a selection on unobservables problem. However by combining matching with DID there is scope for unobservable determinants of participation to be incorporated (Blundell and Costa Dias 2002). The way to implement this estimation is to apply the matching routine to the before and after difference in the outcome variable for each treated and non treated control observation. The estimations are presented in Table 17. As we see, the results obtained previously are confirmed. The FONTAR program has a positive and significant effect on R&D expenditure per employee while it has no impact on total innovation outlays.

5. Concluding Remarks.

In this paper we have looked at the evidence regarding innovation and R&D expenditures of Argentina firms obtained from a recent survey conducted by INDEC-CEPAL. The

quantitative information shows that technological upgrades are implemented mainly through capital goods purchases and licensing (technology transfers). In a very small proportion (between 5 and 15%) innovation is done through investment in research and development. In terms of firm sales, the level of R&D is also very small (around .20%). This value, nevertheless, is in line with other developing economies like Mexico and Chile.

Using the two available surveys we have constructed a panel covering the 1992-2001 period. We observe an increasing trend in mean R&D (per employee or as a share of sales) for the sample of firms during the nineties. This contrast with the sharp decrease observed since 1998 in other innovation expenditures like capital good investment and licensing coinciding with the macroeconomic downturn.

We have employed this data set to test some simple hypotheses regarding the determinants of R&D decisions at the firm level. Clear-cut predictions come from the Schumpeterian tradition in which innovation efforts are positively associated with firm size and market share. We show that these hypotheses are consistent with the Argentine data. We find that both variables are significant and positive and this result is robust to different econometric techniques, different sampling, and also survives when we include industry characteristics and sector dummies. We also find that foreign capital participation raises the level of both R&D and innovation expenditures.

We also investigate the effect on R&D investment of different industry level features like concentration, tariffs, skill intensity and market size. We found that concentration at the level of the industry negatively affects incentives to perform R&D activities. This result is robust to the inclusion of industry dummies. Thus more competitive market environments (as oppose to monopoly market structures) are a positive factor promoting innovation by firms. This competition effect seems to be reinforced by the results coming from the tariff variable. We find that firms operating in industry sectors facing lower tariffs, other factors constant, spend more in R&D. Still this result, nevertheless, does not survive when we introduce sector dummies and there is no effect of tariff on total

innovation expenditures. We also find that industries having a larger participation of skilled labor within the total labor force spend more in innovation activities. With regard to the quantitative impacts of the various variables, we find that industry level determinants have a much larger impact on firm innovation decisions.

Finally we also evaluate the impact of a public sector program, FONTAR, aiming at encouraging R&D activities in the private sector. This program was in full operation from 1997 onwards. We find that this variable comes out positive and significant when included as another regressor, but we suspect that this result can be affected by a selection (endogeneity) bias. Thus, in order to evaluate the causal relationship between these government incentives and firm behavior we perform a Difference in Difference (DID) estimation. In this case, the FONTAR variable does come out positive and significant for R&D expenditures, but we don't find any positive impact for total innovation expenditures. The same conclusion comes when we applied Matching Methods to select for each treated firm a matched individual (or group of individuals) within the non-participating firms. The computed mean difference in R&D expenditures between the treated and the selected control firms comes out significant. We finally combined matching methods and DID when we compare the before and after difference in the R&D and innovation outlays for each treated and matching control observation. The result again suggests that the FONTAR program has had an positive effect on R&D expenditures (and non on total innovation) of around 50 to 70\$ pesos per employee.

Appendix A

Information regarding innovation activities performed by Argentine firms was collected by CEPAL and INDEC in two surveys (Encuesta Nacional sobre la Conducta Tecnológica de las Empresas Industriales Argentinas). The first survey covers the 1992-1996 period while the second collects information between 1998 and 2001. Both surveys have a similar structure so their results can be aggregated. Also both surveys follow closely international standards (like CISSIII, EUROSTAT and OECD) so the results can also be compared with those obtained for other countries. The samples are based upon the 2500 establishments that participate in the industry survey. This feature allows the incorporation in the data set of variables (at the sectoral and individual-firm level) that are obtained from this other industry questionnaire.

The definition used in the survey regarding what constitutes an innovation activity is based upon the recommendations made in the Bogota Manual, which in turns is based upon, and extends the methodology presented in, the Oslo Manual. In particular, the Oslo Manual proposes a rather narrow, technologically driven, definition of innovation. It comprises *implemented* new products and /or processes and/or significant technological improvements in products and processes. The term “technological” is associated to objective improvement in the performance of a product or process, which can be associated (especially in the case of processes) to “..a measurable change in output, such as productivity or sales..” . The Bogota manual introduced some adaptations /extensions to this basic methodology. One of those is that innovation activities taken by a firm do not need to be already implemented (that is, introduced in the market or used within a production process) to be considered as such. A second extension is that the definition also includes “purely” organizational, management and/or marketing innovation (not directly related to technological improvements).

Based upon these principles and definitions the survey asks firms to classify its innovation activities in terms of two dimensions. First, in terms of its final objective. That is, if a determinate innovation activity aims at improving: (i) product; (ii) production

process; (iii) organizational/management changes or (iv) commercialization/marketing routines. Second, the way the innovation activity is implemented: (i) internal R&D, (ii) external R&D; (iii) purchase of capital goods; (iv) hardware; (v) software; (vi) licensing of a new technology; industry and engineering design, (vii) new management techniques; (viii) training; (ix) consulting services.

The survey also asks if the firm has got a new patent as a consequence of its innovation activities and also there is a part dedicated to the relationship with the National Innovation System. Thus it is asked if the innovation activities of the firm have been developed in the context of a relationship with Universities, Technological Centers, Laboratories, Suppliers, Clients, the Foreign Mother Company, Public Agencies or other Innovation Programs run by the government. Finally there are a series of questions regarding firm characteristics (size, educational level of workers, production, sales, investment, exports, imports, etc.).

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Table 1. Total expenditure in innovation activities and main economic indicators

Innovation indicators	1st Survey(1639 firms)		2nd Survey(1668 firms)	
	1992	1996	1998	2001
Total expenditure in innovation activities (TEIA)	1,435,067	1,766,429	867,234	754,104
TEIA as % of total sales	2.97	3.7	2.12	1.68
Total employment	355,199	350,414	260,795	253,852
Employment in IA/ total employment (%)	1.18	1.4	1.4	1.56
Exports as % of total sales	12.72	17.98	15.25	18.48
Imports as % of total sales	13.5	16.23	16.12	14.24
Investments as % of total sales	7.13	8.22	10.16	5.59

Source: CEPAL, INDEC, SeCyT (1998), (2003)

Table 2. Composition of Innovation Expenditures (IE).						
	1st Survey(1639 firms)					
	1992			1996		
	Amount*	% of TEIA	% sales	Amount*	% of TEIA	% sales
I&D	51,709	4.0%	0.15%	77,061	5.0%	0.16%
Embodied IE	1,067,978	74.0%	1.94%	1,064,761	63.0%	2.61%
Capital good purchases	1,024,694	71.0%	1.77%	977,865	58.0%	2.36%
Hardware	43,284	3.0%	0.17%	86,896	5.0%	0.25%
Disembodied IE	315,376	22.0%	0.88%	537,637	32.0%	0.95%
Software	43,874	3.0%	0.13%	115,092	7.0%	0.17%
Licensing and technology transfers	118,141	8.0%	0.34%	201,988	12.0%	0.34%
Ingeneering and industry design	49,848	4.0%	0.17%	79,265	4.0%	0.20%
Training	70591	5.0%	0.14%	70591	4.0%	0.10%
Consulting	32,922	2.0%	0.10%	70,699	4.0%	0.14%
Total	1,435,067	100.0%	2.97%	1,766,429	100.0%	3.72%
	2st Survey(1639 firms)					
	1998			2001		
	Amount*	% of TEIA	% sales	Amount*	% of TEIA	% sales
I&D	52,104	5.8%	0.17%	110,021	16.6%	0.26%
Embodied IE	651,022	72.3%	1.56%	381,187	57.4%	1.03%
Capital good purchases	607,016	67.4%	1.47%	351,799	53.0%	0.97%
Hardware	44,006	4.9%	0.09%	29,388	4.4%	0.06%
Disembodied IE	197,519	21.9%	0.39%	172,399	26.0%	0.39%
Software	23,920	2.7%	0.06%	23,271	3.5%	0.06%
Licensing and technology transfers	92,255	10.2%	0.15%	67,213	10.1%	0.13%
Ingeneering and industry design	50,576	5.6%	0.11%	47,561	7.2%	0.12%
Training	18,138	2.0%	0.04%	18,811	2.8%	0.04%
Consulting	12,630	1.4%	0.03%	15,543	2.3%	0.04%
Total	900,645	100.0%	2.12%	663,607	100.0%	1.68%

*in current thosands of US\$

Source: CEPAL, INDEC, SeCyT (1998), (2003)

Table 3				
Year	Number of Firms	Mean R&D/Sales	Mean R&D/Employees	% of Firms with R&D =0
1992	1,528	0.16	11.42	81.68
1996	1,627	0.21	17.58	75.41
1998	1,518	0.36	28.43	73.85
1999	1,075	0.27	54.04	72.37
2000	1,141	0.30	37.18	72.13
2001	1,568	0.43	30.11	71.49

Table 4				
Year	Number of Firms	Mean Innovations /Sales	Mean Innovations/ Employees	% of Firms with Innovations =0
1992	1,528	5.51	336.75	25.72
1996	1,627	4.87	468.87	21.76
1998	1,518	2.36	307.61	48.42
1999	1,075	1.82	419.41	50.05
2000	1,141	2.18	361.89	48.99
2001	1,568	1.88	192.47	44.96

Table 5. Industry average values of R&D and Innovation Expenditures. Selected years

Industry	1992		1998		2001		%01/92	%01/92
	R&D/L	TEIA/L	R&D/L	TEIA/L	R&D/L	TEIA/L	R&D/L	TEIA/L
Food and Beverages	4.20	317.46	11.10	212.64	14.01	144.24	233.51	-54.56
Tobacco	77.55	282.99	2.25	52.32	4.47	105.75	-94.24	-62.63
Textil products	2.73	220.93	8.23	171.61	9.53	86.32	249.02	-60.93
Apparel	1.39	66.86	7.28	24.76	7.48	23.37	436.41	-65.05
Leather, footwear	9.22	69.02	9.93	48.61	6.38	37.61	-30.85	-45.50
Wood production (non furnitures)	0.26	74.71	19.21	85.33	10.34	93.23	3946.31	24.80
Paper production and paper products	1.03	224.34	15.47	899.68	19.10	574.62	1748.11	156.14
Printing and publishing	2.44	267.20	12.05	335.89	16.53	170.58	577.01	-36.16
Petroleum destilery	28.51	456.36	168.18	328.69	167.03	476.18	485.81	4.34
Chemical products	42.41	395.70	87.23	784.68	114.88	499.80	170.85	26.31
Rubber and Plastic products	6.40	563.16	10.31	440.75	14.05	188.63	119.65	-66.50
Non metal mineral products	8.44	640.99	23.86	505.74	19.30	272.67	128.77	-57.46
Basic metals	7.82	154.15	19.70	280.51	14.80	171.04	89.40	10.96
Metal products (Non machinery and equipment)	6.33	221.38	62.19	252.49	49.93	150.51	688.67	-32.01
Machinery and equipment	10.11	160.19	26.59	121.56	24.72	107.13	144.55	-33.12
Computer , Accounting and Office Machinery	0.00	213.36	214.29	266.07	164.38	204.11	-	-4.33
Engines and Electric equipment	11.03	1317.67	19.45	112.91	30.58	83.97	177.35	-93.63
Audio, video, TV, and communication equipment	90.13	411.80	81.92	491.07	22.87	337.99	-74.63	-17.92
Medical, Ophtalmic, watches, clocks,etc.	12.51	190.54	17.99	196.90	20.17	112.21	61.21	-41.11
Motor vehicles and equipment	22.76	470.52	49.10	421.52	34.68	255.81	52.40	-45.63
Other Transportation equipment	2.13	120.15	13.52	35.20	33.03	43.00	1454.04	-64.21
Furnitures and manufacturing industries	10.84	172.53	23.37	108.29	15.26	62.91	40.73	-63.54

R&D / Employees

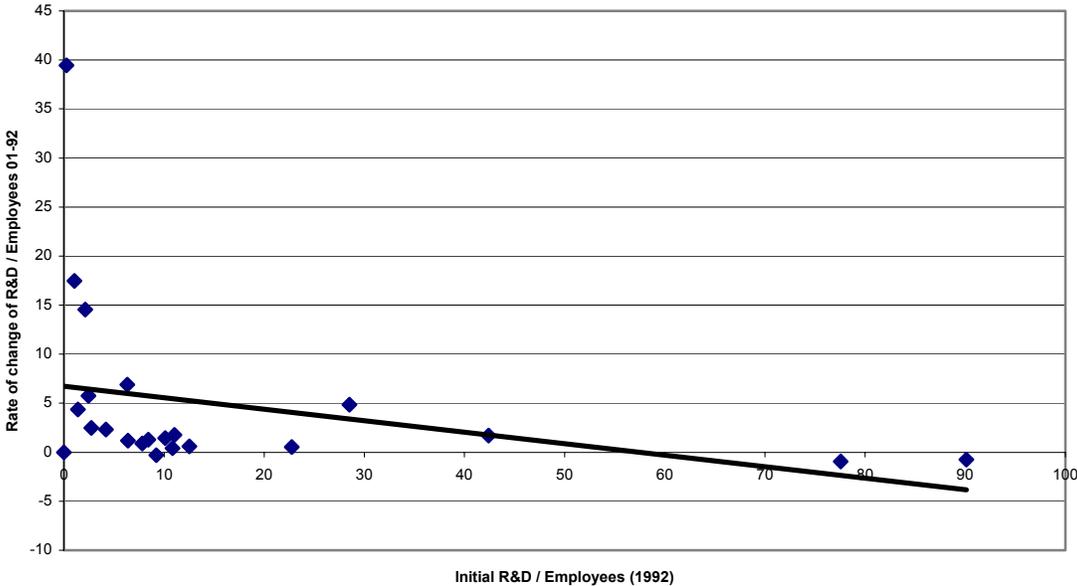


Figure 2. R&D - Size of Firms

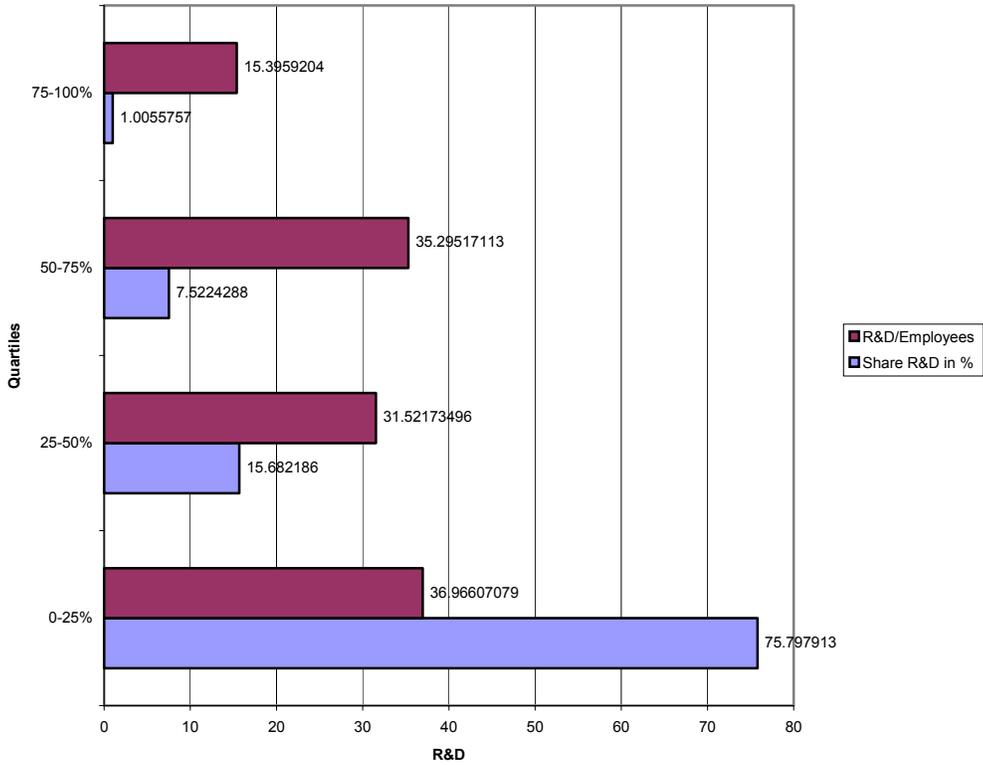


Table 6. Top ten firms in term of R&D per employee

	0-25%	25%-50%	50%-75%	75%-100%
	2 Digit-ISIC	2 Digit-ISIC	2 Digit-ISIC	2 Digit-ISIC
1	28	29	23	28
2	24	29	15	24
3	15	31	24	15
4	24	29	36	21
5	32	15	26	15
6	24	29	24	24
7	15	29	27	29
8	19	31	25	28
9	25	34	24	26
10	24	24	31	24

Table 7. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
R&D / Employees	8468	27.99	233.68	0.00	17912.16
Innovations / Employees	8468	344.13	2086.47	0.00	101873.70
Employees (size)	8468	212.43	476.54	1.00	18401.00
Market share	8468	0.03	0.07	0.00	0.96
Foreign capital	8468	13.98	32.67	0.00	100.00
Average tariff	8468	0.17	0.05	0.01	0.35
Concentration	8468	0.72	0.21	0.20	1.00
Skills	8468	0.33	0.12	0.00	1.00
VBP*	8468	1610.00	1630.00	7.75	11500.00
Fontar	8468	0.03	0.16	0.00	1.00

* In millions

Table 8. Pooled Regressions. Probit: Marginal effects

	R&D expenditures/ Employees					
Total employment	0.289	0.315	0.312	0.326	0.309	0.32
	(0.025)***	(0.026)* **	(0.026)***	(0.027)***	(0.026)***	(0.027)***
Employment square	-0.047	-0.052	-0.05	-0.053	-0.051	-0.053
	(0.006)***	(0.006)* **	(0.006)***	(0.006)***	(0.006)***	(0.006)***
Market Share	0.19	0.193	0.109	0.136	0.122	0.152
	(0.074)**	(0.079)* *	-0.08	-0.083	-0.08	(0.082)*
Foreign capital participation	0	0	0	0	0	0
	(0.000)***	0	(0.000)**	0	(0.000)**	0
Average Tariff			-0.438	0.133	-0.421	0.12
			(0.100)***	-0.114	(0.100)***	-0.114
Concentration			-0.047	-0.031	-0.048	-0.031
			-0.029	-0.035	-0.029	-0.035
Skills			0.28	0.155	0.27	0.142
			(0.041)***	(0.051)***	(0.040)***	(0.051)***
Industry market size			0	0	0	0
			(0.000)***	(0.000)**	(0.000)***	(0.000)**
FONTAR					0.314	0.276
					(0.034)***	(0.036)***
Dummy Industry Level	No	Yes	No	Yes	No	Yes
Dummy Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8468	8468	8468	8468	8468	8468
Robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 9. Pooled Regressions. Tobit: marginal effects

	R&D / Employees					
Total employment	0,06133 (0.0069)***	0,0625 (0.0067)***	0,0597 (0.0071)***	0,0605 (0.0069)***	0,0586 (0.007)***	0,0589 (0.0069)***
Employment square	-0,00001 (0.000)***	-0,00001 (0.000)***	-0,00001 (0.000)***	-0,00001 (0.000)***	-0,00001 (0.000)***	-0,00001 (0.000)***
Market Share	38,15 (20.69)**	38,48 19,99	41,25 (21.90)**	42,88 (21.21)**	45,36 (21.71)**	47,43 (21.07)**
Foreign capital participation	0,1779 (0.0437)***	-0,008 (0.0421)***	0,1316 (0.0431)***	0,0012 0,042	0,1454 (0.0428)***	0,0161 0,0417
Average Tariff			-101,68 (30.85)***	52,06 33,09	-95,62 (30.64)***	49,15 32,9
Concentration			-27,54 (8.367)**	-21,01 (9.844)*	-27,91 (8.303)**	-20,75 (9.78)*
skills			104,37 (12.42)***	53,91 (14.52)**	100,85 (12.34)***	50,53 (14.45)**
Industry market size			0 0	0 0	0 0	0 0
FONTAR					79,05 (7.23)***	62,77 (6.86)***
Dummy ISIC 2 Digits	No	Yes	No	Yes	No	Yes
Dummy Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8468	8468	8468	8468	8468	8468
Robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 10. Estimated quantitative impact on R&D expenditure/employee

Explanatory variables	mean X	Estimated marginal effect	Estimated change (10% increase in X)
Size	212	0.0589	1.14
Size square	212	-0.00001	
market share	0.033	47.3	0.15
foreign part	14.01	0.14	0.19
Concentration	0.72	-20.75	-1.494
Tariffs	0.17	-95.6	-1.6252
Skill	0.32	50.53	1.61696
VBP	1.61E+09	-	-
Fontar	0.027	62	62

Table 11. Pooled Regressions. Probit: marginal effects

	Innovations / Employees					
Total employment	0,637 (0.047)***	0,645 (0.049)***	0,645 (0.049)***	0,646 (0.050)***	0,635 (0.049)***	0,634 (0.050)***
Employment square	-0,112 (0.010)***	-0,113 (0.010)***	-0,111 (0.010)***	-0,112 (0.010)***	-0,112 (0.010)***	-0,112 (0.010)***
Market Share	0,18 -0,123	0,339 (0.135)**	0,18 -0,138	0,313 (0.145)**	0,194 -0,137	0,326 (0.144)**
Foreign capital participation	0,002 (0.000)***	0,001 (0.000)***	0,001 (0.000)***	0,001 (0.000)***	0,001 (0.000)***	0,001 (0.000)***
Average Tariff			-0,429 (0.120)***	0,005 -0,136	-0,41 (0.120)***	-0,005 -0,136
Concentration			-0,154 (0.034)***	-0,128 (0.041)***	-0,155 (0.034)***	-0,129 (0.041)***
skills			0,371 (0.052)***	0,295 (0.063)***	0,359 (0.052)***	0,281 (0.062)***
Industry market size			0,000 (0.000)***	0,000 (0.000)**	0,000 (0.000)***	0,000 (0.000)**
FONTAR					0,22 (0.025)***	0,201 (0.027)***
Dummy Industry Level	No	Yes	No	Yes	No	Yes
Dummy Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8468	8468	8468	8468	8468	8468
Robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 12. Pooled Regressions. Tobit: marginal effects

Marginal Effects	Innovations / Employees					
Employment	0,5161 (0.0675)***	0,4917 (0.0691)***	0,4843 (0.07)***	0,4791 (0.0708)***	0,4799 (0.0699)***	0,4716 (0.0708)***
Employment square	-0,0001 (0.000)***	-0,00009 (0.000)***	-0,00009 (0.000)***	-0,00009 (0.000)***	-0,00009 (0.000)***	-0,00009 (0.000)***
Market Share	1.006,62 (202.37)***	1.160,98 (207.99)***	1.094,36 (217.431)***	1.116,17 (220.54)***	1.113,92 (217.19)***	1.138,93 (220.41)***
Foreign capital participation	3,1529 (.4161)***	1,956 (.4243)***	2,831 (0.418)***	1,973 (0.4246)***	2,9035 (0.4186)***	2,0488 (0.4248)***
Average Tariff			-317,28 286,56	494,09 (318.25)**	-294,54 286,35	480,00 (318.02)**
Concentration			-170,56 (77.76)**	24,049 94,1	-172,17 (77.68)**	24,43 94,02
Skills			760,96 (115.83)***	557,61 (140.24)***	749,28 (115.73)***	544,47 (140.17)***
Industry market size			0 0	0 0	0 0	0 0
FONTAR					382,86 (77.77)***	323,78 (77.30)***
Dummy Rama 2 Digits	No	Yes	No	Yes	No	Yes
Dummy Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8468	8468	8468	8468	8468	8468
Robust standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 13. Estimated quantitative impact on innovation expenditures/employees

Explanatory variables	mean X	Estimated marginal effect	Estimated change (10% increase in X)
Size	212	0.471	9.09
Size square	44944	-0.00009	
market share	0.033	1138.9	3.75837
foreign part	14.01	2.0488	2.8703688
Concentration	0.72	-172.17	-12.39624
tariffs	0.17	-	-
Skill	0.32	544.47	17.42304
VBP	1.61E+09	-	-
Fontar	0.027	323.7	323.7

Table 14. Difference-in-Difference Estimation						
	R&D / Employees			Innovations / Employees		
Controls by:	Only Fontar	Firm Level	Industry Level	Only Fontar	Firm Level	Industry Level
FONTAR	64.862	67.532	54.283	74.125	99.617	52.049
	(15.388)***	(15.395)***	(15.604)***	-108.525	-107.462	-109.276
Employment		-0.085	-0.084		-0.673	-0.669
		(0.018)***	(0.018)***		(0.128)***	(0.128)***
Employment square		0	0		0	0
		(0.000)***	(0.000)***		(0.000)***	(0.000)***
Market Share		29.978	29.377		-523.513	-515.51
		-39.813	-39.715		(277.897)*	(278.119)*
Foreign capital participation		0.338	0.33		5.263	5.245
		(0.112)***	(0.112)***		(0.784)***	(0.784)***
Average tariff			35.817			402.238
			-48.481			-339.506
Skills			0			0
			0			0
VBP			0			0
			(0.000)**			0
Constant	5.94	19.422	-3.755	6.04	128.706	4.305
	-3.699	(5.238)***	-10.678	-26.084	(36.564)***	-74.775
Observations	3834	3834	3828	3834	3834	3828
Number of firmid	639	639	638	639	639	638
Standard errors in parentheses						
* significant at 10%; ** significant at 5%; *** significant at 1%						

Table 15. Estimation of the Propensity Score

	FONTAR
Average Tariff	-0.066
	-0.88
Employment	0
	(0.000)**
Market Share	-2.006
	-1.395
Foreign capital participation	-0.006
	(0.002)***
Skills	0.653
	(0.194)***
Engineers	0
	-0.001
Exports/sales	0.92
	-2.89
Imports/sales	3.467
	-3.875
Constant	-2.025
	(0.192)***
Observations	1964
Standard errors in parentheses	
* significant at 10%; ** significant at 5%; *** significant at 1%	

Table 16. Matching Methods

**ATT estimation with Nearest Neighbor Matching method
(random draw version)**

Variable	n. treat.	n. contr.	Average value of Treated	Average Value Controls	ATT	Std. Err.	t
R&D / Employees	67	66	80,71635	19,61139	61,105	35,108	1,741
TEIA / Employees	67	66	242,8777	319,4978	-76,62	195,07	-0,393

Note: the numbers of treated and controls refer to actual nearest neighbor matches

ATT estimation with the Radius Matching method

Variable	n. treat.	n. contr.	Average value of Treated	Average Value Controls	ATT	Std. Err.	t
R&D / Employees	57	349	90,1503	14,68512	75,465	40,48	1,864
TEIA / Employees	57	349	260,5992	175,787	84,812	80,684	1,051

Note: the numbers of treated and controls refer to actual matches within radius

**ATT estimation with the Kernel Matching method
Bootstrapped standard errors**

Variable	n. treat.	n. contr.	Average value of Treated	Average Value Controls	ATT	Std. Err.	t
R&D / Employees	67	1897	80,716352	25,692679	55,024	31,929	1,723
TEIA / Employees	67	1897	242,87769	223,40897	19,469	63,488	0,307

**Table 17. Combining DID and Matching
Differences in R&D and TEIA:1998-96 and 2001-96**

**ATT estimation with Nearest Neighbor Matching method
(random draw version)
Analytical standard
errors**

Variable	n. treat.	n. contr.	Average value of Treated	Average Value Controls	ATT	Std. Err.	t
R&D / Employees	66	65	78,10749	19,93842	58,169	35,557	1,636
TEIA / Employees	66	65	242,6538	326,0771	-83,423	198,012	-0,421

Note: the numbers of treated and controls refer to actual nearest neighbor matches

**ATT estimation with the Radius Matching method
Analytical standard
errors**

Variable	n. treat.	n. contr.	Average value of Treated	Average Value Controls	ATT	Std. Err.	t
R&D / Employees	54	295	90,4772	13,8977	76,58	42,685	1,794
TEIA / Employees	54	295	265,0559	199,4945	65,561	88,288	0,743

Note: the numbers of treated and controls refer to actual matches within radius

**ATT estimation with the Kernel Matching method
Bootstrapped standard errors (500 Reps)**

Variable	n. treat.	n. contr.	Average value of Treated	Average Value Controls	ATT	Std. Err.	t
R&D / Employees	66	1688	78,107493	25,937459	52,17	33,948	1,537
TEIA / Employees	66	1688	242,65385	244,58749	-1,934	61,529	-0,031