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Abstract

This paper uses two sources of information and different methodologies to analyze the causal effect of product and process innovation on productivity in the Chilean manufacturing industry during the past decade. In general, the evidence suggests there is not a contemporaneous effect of product innovation on productivity, but there is a positive effect of process innovation. This not-significant effect of product innovation contrasts with evidence of studies for other countries. However, the results show the presence of lagged effects product innovation on productivity two years after innovation. Compared with the case of developed countries, this evidence might be consistent with a very slow process of "learning by doing" on the part of Chilean firms with regard to mastering new technologies. These slow and frequently uncertain gains in productivity could help to explain the low levels of investment in research and development (R&D) activities by Chilean firms.

JEL Classifications: D22, D24, D92

Keywords: Productivity, Innovation, Investment, Research and development, Chile

1. Introduction

The relationship between productivity and research and development (R&D) has been a topic of inquiry since the early work of Schultz (1953) and Griliches (1958). Since then, this area of research has produced a significant amount of empirical and theoretical work. Several recent theoretical models have assigned a substantial role to R&D as an engine of productivity and hence, economic growth (Romer, 1990; Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; Aghion and Howitt, 1992). From an empirical perspective, the literature has found that almost 50 percent of per capita income and growth rate differentials across countries can be explained by differences in total factor productivity, or TFP (Hall and Jones, 1999). But most importantly, the literature suggests that R&D activities can explain up to 75 percent of TFP growth rates once externalities are considered (Griliches, 1995).

The rapid economic growth of East Asian economies has brought attention to the role of R&D activities on economic development. Korea, for example, had an R&D-to-GDP ratio close to 0.35 percent in the 1960s. This figure has increased almost constantly in the subsequent four decades, reaching 2.4 percent in recent years. This has been credited as one of the causes of the significant TFP and GDP per capita growth experienced by Korea since the 1960s.

In contrast, Latin American and Caribbean countries have exhibited a very modest rate of economic growth during the past decade, despite unusually favorable economic conditions. This poor performance is not new in the region. Indeed, during the past four decades, per capita income in the region grew 1.44 percent per year, while TFP grew by a modest 0.29 percent. Chile, among other countries in the region, lags behind East Asian countries over the same time period (see Table 1).

Latin America’s poor economic performance can be understood by examining the R&D effort of the region compared with other regions of the world (see Table 2). This indicator shows that the OECD’s decade-average during 1960–2000 fluctuated between 1.87 percent and 2.25 percent. In the case of Scandinavian countries, the R&D effort increased from 1.12 percent in the 1960s to 2.71 percent in the 1990s. In contrast, R&D expenditure in Latin America fluctuated between 0.36 percent and 0.52 percent of GDP during the same period. Low private-sector investment in R&D in the region has been explained by financial market failures, low human capital endowments, macroeconomic volatility, insufficient provision of public goods, and shortcomings in the regulatory framework, among other reasons.[1]

This paper aims to contribute to a better understanding of the relationship between R&D and productivity in Latin America, by focusing on the Chilean experience. At first glance, the Chilean case does not deviate much from the historical pattern of Latin America. Although Chile ranked at the top of regional positions for some indicators during the 1990s, this was not true during the preceding decades. Furthermore, when compared to developed countries in most of the R&D measures, Chile lags behind significantly. Table 3 shows R&D expenditure over GDP and R&D per capita (in 1996 constant dollars). Although in recent years Chilean R&D expenditure has surpassed 0.6 percent of GDP, it is still below the 0.84 percent that Brazil averaged for the 1990s and is very close to the 0.52 percent regional average during the same period. By the same token, the average R&D expenditure per capita in the region was close to US$33 during the 1990s. The Chilean average was US$46, still below the US$54 that Brazil averaged during the same period. With respect to sources of funding for R&D, the main source by 2004 was the private sector with 46 percent, according to UNESCO; the government and universities financed the rest.

Regarding R&D output, Latin American countries underperform compared to leading countries, and Chile is not an exception. Consider the number of patents granted in the United States to researchers not living in the United States (Table 4). Researchers across all of Latin America obtained 258 patents during 2000–04, while Australian researchers received 858 patents. According to Bravo-Ortega and García (2007), Brazil obtained an average of 108 patents, Argentina 53.6, and Chile a modest 13 patents per year.

With the exception of a few studies, there is not much evidence on the impact of research activities on productivity in Chile (Benavente, 2006). Previous results show that the link between R&D and firms' productivity is very weak, but little is known about the causes of such weakness. The main objective of this paper to establish whether Chilean private investment in R&D has an impact on productivity growth, to analyze the extent and characteristics of that impact, and to determine how and why such an impact is taking place.

The paper is structured as follows. In the second section, we estimate the effect of innovation on productivity using a variation of the framework developed by Crépon, Duguet, and

[1] Innovation Strategy, National Innovation for Competitiveness Council of Chile, Volumes 1 and 2.

Mairesse (1998), known as the CDM model. In particular, we closely follow the methodology used by Griffith et al. (2006), which allows us to compare our results with those for four European countries. In the third section, we use information on changes in firm product mix during 1996–2003 to analyze the relationship between product innovation and total factor productivity. The fourth section summarizes our findings.

2. Innovation, R&D, and Productivity: The CDM Model

Following the empirical research line initiated by the influential work of Crépon, Duguet, and Mairesse (1998) we examine the empirical relationship between R&D, innovation, and firm productivity in this section. Our approach is based on a multi-equation model that takes into account the whole process of innovation, thereby considering firms' decisions to engage in R&D activities, the results of those efforts, and their impact on productivity.

2.1 Methodology

The baseline model consists of four equations: (i) the firm's decision to invest in R&D, (ii) the intensity of R&D, (iii) the knowledge production function linking R&D intensity and innovation outcome, and (iv) the output production function, in which firm productivity is a function of innovation outcome.

We closely follow the estimation approach of Griffith et al. (2006). First, we estimate a generalized Tobit that considers the decision to invest in R&D and the amount invested. Second, we use the predicted value of R&D intensity as an explanatory variable in the knowledge production function, where the innovation outcome is measured by two categorical variables that account for product and process innovation. Finally, the predicted values of innovation outcomes are used as explanatory variables in the output production function.[2] Given that Chilean surveys differ from European ones, we explicitly mention the source of these differences when defining the dependent and explanatory variables.

[2] This model may be estimated using alternative econometric techniques as Asymptotic Least Squares. Actually, the original paper by Crépon, Duguet, and Mairesse (1998) uses this methodology. However, recent works on this issue tend to prefer the less computationally intensive technique of estimating the three components of the model separately using instrumental variables (Griffith et al., 2006; Hall, Lotti, and Mairesse, 2008).

2.1.1 R&D Investment

We rely on a generalized Tobit framework to model the decision to invest and the amount invested in research activities. Hence, there are two linked equations: (i) the decision to invest in R&D, and (ii) the amount of resources involved, measured as R&D expenditure per employee (in logs). More precisely, we assume that there exists a latent dependent variable R_i^* for the firm *i* given by the following equation:

$$R_i^* = X_{1i}^{'}\beta + \varepsilon_i \qquad (1)$$

where $X_{1i}^{'}$ is a vector of explanatory variables, β is a vector of parameters, and ε is an error term. The econometrician observes that resources are invested in R&D activities if R_i^* is positive or larger than a given threshold.

We assume the following selection equation describing whether or not a firm is investing in R&D:

$$RD_i = 1 \quad if \quad RD_i^* = W_i^{'}\alpha + e_i > c, \quad and \quad 0 \quad otherwise. \qquad (2)$$

where RD is an observed binary variable equal to zero for firms not performing R&D and 1 for those investing in R&D, RD_i^* is the corresponding latent variable such that a firm decided to invest in R&D if it is above a certain threshold denoted by c, and W is a vector of explanatory variables.

Conditional on investing in R&D, the observed R&D investment (R_i) is given by:

$$R_i = \begin{pmatrix} R_i^* = Z_i^{'}\beta + \varepsilon_i \quad if \quad RD_i = 1. \\ 0 \quad if \quad RD_i = 0. \end{pmatrix} \qquad (3)$$

The system of equations (2) and (3) is estimated as a generalized Tobit model by maximum likelihood. The vector of explanatory variables W and Z follows closely those used by Griffith et al. (2006). Therefore, we model the firm’s decision on whether to invest in R&D, taking into account the following explanatory variables:

- International competition: defined as the export to sales ratio. This variable is used to capture the exposure of a firm to international competition. It is different than that used by Griffith et al. (2006). In that work, a dummy variable identifies whether the international market is the firm's most important market.
- Appropiability conditions: defined as a dummy variable that takes the value 1 if the firm declares that easiness of imitation is an obstacle of high importance for innovation. This variable is aimed to capture the effect of legal and formal protection of intellectual property in the country. In contrast to Griffith et al. (2006), Chilean surveys lack information on formal and strategic protection.
- Firm size: includes a set of four dummy variables for firms with 50 to 99 workers (size1), 100 to 250 workers (size2), 250 to 999 workers (size3), and more than 1,000 workers (size4). The base category consists of small firms with fewer than 50 workers.
- Technological opportunities and other invariant industry characteristics are controlled by using dummy variables for each of the 2-digit industries.
- The set of explanatory variables for R&D intensity includes some of the variables defined above (international competition and industry dummies) and the following additional variables:
  - Cooperation: is captured by a dummy variable that takes the value 1 if the firm has some cooperative arrangement on innovation activities. In the Chilean case, this variable specifically measures the existence of formal contracts with universities or technological institutes.
  - Public resources: defined as a dummy variable that indicates whether the firm uses public resources for funding R&D investments. In contrast to Griffith et al. (2006), Chilean surveys do not distinguish between regional and national sources of funding.[3]
  - Demand conditions: four variables related to the importance of quality standards and environmental considerations for engaging in innovation are considered. All these variables are defined as sectoral level shares. The

[3] For European countries the surveys distinguish public financing from local and national governments and resources from the European Union.

first variable is the share of firms for which improvement of quality through the implementation of standards (ISO 9000 and others) was of high/medium importance. The second variable is the share of firms for which quality improvement was of low importance for innovation. The third variable is the share of firms for which environmental concerns were of high/medium importance for innovation. And finally, the fourth variable is the share of firms for which environmental concerns were of low importance for innovation. The reference group in both cases is the share of firms for which quality and environment, respectively, were qualified as not important.[4]

- Sources of information: six possible sources are considered resulting in a set of six dummy variables that take the value of 1 when the firm considers the source as being of high importance for innovation. The six different sources are: (i) internal sources within the firm, (ii) internal sources within the group to which the firm belongs, (iii) universities, (iv) public institutes, (v) suppliers and customers, and (vi) competitors. Two of these variables are different from the variables used by Griffith et al. (2006). First, they have data on the importance of the government as a source of information. We replace that variable with one listing public institutes as a source of information. Second, because Chilean surveys ask about both customers and suppliers in the same question, we cannot distinguish between the two and must therefore include both in the same category.

Several papers have included a proxy for market competition as an explanatory variable (Crépon Crépon, Duguet, and Mairesse, 1998; Benavente, 2006). Traditionally this effect is captured by the market share of the firm. Therefore, in our robustness check, we consider the firm's market share (in logs) as an explanatory variable in R&D decisions.

[4] The majority of the questions in the Chilean surveys use a scale with five possible values, from 0 (no importance) to 4 (highest importance). In this case, values of 3 and 4 are considered to have medium/high importance and values of 1 and 2 have low importance.

2.1.2 Knowledge Production Function

In general, it is assumed that innovative output is related to improvements in a firm's productivity. There are, however, several ways to proxy innovation output. The most common proxies are the number of patents and the share of innovative sales. Following Griffith et al. (2006), we use two indicators of innovation output. The first indicator relates to process innovation, and is defined as a dummy variable that takes the value 1 when the firm has introduced significant improvements in the technological process during the past three years. The four available Chilean surveys, however, ask different questions regarding process innovation. In the last three surveys, firms are asked whether they have introduced a new technological process for the market. The second indicator relates to product innovation and is defined as a dummy variable that takes the value 1 for those firms that have introduced new products into the market during the past three years.

The surveys include three questions related to product and process innovation. In the case of product innovation, firms are also asked about technological improvements of products and the introduction of a new product that may be new for the firms but not new for the market. For innovation process, the approach is similar. Firms are asked about partial but important technological improvements and about the introduction of technological process that may be new for the firm, but not new in the market. Our choice is based on the idea of innovations that are new to the firm and the market.

We estimate two separate probit models for product and process innovation. These in turn can be modeled as follows:

$$I_i = \delta R_i^* + Y_i^{'}\gamma + \mu_i \tag{4}$$

where I_i is equal to 1 if the firm has introduced an innovation. R_i^* is the predicted value of the firm's innovative effort (log of R&D per worker) from the estimated generalized Tobit equations described above, and $Y_i^{'}$ is a vector of explanatory variables. This instrumental variable estimation, given by the inclusion of the predicted value of R_i^*, takes into account the potential endogeneity of R&D investment. Following Griffith et al. (2006), the set of explanatory variables considers:

- The predicted values of R&D intensity obtained from the Tobit model.
- Investment intensity, defined as investment in machinery per employee.[5] It is assumed that this variable only affects process and not product innovation. The idea is that new machinery may challenge firms to change their technological process, but not necessarily the type of product they produce.
- The same set of variables capturing demand conditions used for the equation of determinants of R&D intensity.
- The four dummy variables for firm's size
- Dummy variables for each 2-digit industry.

The basic identifying assumption in this methodology is that there are some variables affecting the decision to invest in R&D that do not affect the innovation outcome. There are several variables—included in R&D decisions but not innovation outcomes—for which this assumption is likely to hold. Let us consider, for example, the use of public resources. It can be argued that, in the presence of financial constraints, public resources are useful for financing R&D. However, it is difficult to argue that public financing may directly increase the probability of introducing new products or new technological process. By the same token, the variables that identify the sources of innovation are likely to affect the resources invested in R&D, but not necessarily the innovation outcomes.[6]

2.1.3 Output Production Function

Assuming a Cobb-Douglas production function, the effect of innovation on productivity may be estimated with the following specification:

$$y_i = \alpha_1 k_i + \alpha_1 I_i + \upsilon_i \tag{5}$$

[5] For the 2001 and 2005 surveys, we are restricted to using total investment. We do not have information disaggregated by type of investment.

[6] The National Survey of Innovation (EIT) also provides information on the importance of innovated products on sales and exports. The first one has been used in previous work (Benavente, 2006; Crépon, Duguet, and Mairesse, 1998). We have also used this information to estimate a linear model with this innovation measure as a dependent variable. The results, in general, do not show any impact of the innovation outcomes defined in this way on productivity.

where y is labor productivity (log of sales per worker), k is log of capital per worker,[7] and I is the knowledge input proxied by product and process innovation. As discussed below, we also use the importance of product innovations in sales and exports as a proxy for knowledge inputs. One way to deal with the endogeneity of this variable is to introduce in equation (5) the predicted values of the innovation variables from equation (4). As in the previous equation, the identification assumption is that some variables included in the knowledge production function, (specifically lower appropriability and the interaction with suppliers and customers) affect the probability of introducing innovations, but do not directly affect the productivity of the firms. As additional covariates for explaining productivity, we include the full set of size and industry dummy variables.

2.2 Data Description

The main source regarding innovation activities in Chile is the National Survey of Innovation (EIT) carried out by the National Institute of Statistics. The survey was conducted in 1995, 1998, 2001, and most recently, in 2005. The questionnaire follows the guidelines of the Frascati Manual developed by the OECD. Though there are some variations over time in the number and types of questions, the main structure of the survey is similar across the different versions. The questions are organized into the following main sections: (i) the types of innovations that the firm has carried out in the past three years, (ii) the goals of those innovations, (iii) the source(s) of the idea to innovate, (iv) the purchasing of equipment, (v) the obstacles to innovation, (vi) links with scientific and technological institutions, (vii) the importance of innovation in firm business, (viii) the cost and financing of innovation, (ix) expenditure in R&D, and (x) perspectives concerning future innovations.

We have access to all four waves of the EIT, as well as several versions of the Annual Survey of Manufactures (ENIA), managed by the official Chilean statistics agency (INE). These two sources of information have been merged at the plant level using an identification number for plants in both datasets. Unfortunately, there was a change in the plant identification system during the period and the best way to match this information would be to use panel 1999-2000 for the 1995 and 1998 EITs, panel 1996-2003 for the 2001 EIT, and panel 2000-2006 for the 2005 EIT. After intensive work with the different sources of information, this is the most

[7] Given that we have information on capital per worker for almost the entire period, we prefer this variable to gross investment per worker used in previous studies (Griffith et al., 2006).

confident matching that we could undertake. The advantage of this matching between both sources of information is that we can use the data to analyze not only the impact of innovation on current productivity, but also to determine whether there are lagged effects. In fact, for most of the four surveys, we are able to estimate the lagged effect of innovation on productivity.

We present estimations for pooling the four different surveys. We include survey-year specific effects to control for time-varying shocks that may affect all plants. A better alternative would have been to exploit the panel dimension of the data. This would allow us to control for firm-specific heterogeneity and to analyze dynamic issues more properly. However, the number of firms common to all the different surveys is too small to give meaningful results.[8]

Because the ENIA only covers manufacturing industries, our study of the relationship between innovation and productivity would have been constrained to the manufacturing sector had we focused solely on the ENIA. The EIT is intended to be representative at 2-digit level industries. Figure 1 shows the distribution of plants across the nine industries for each survey. In general, the distribution varies across surveys, but there are two industries that represent a large proportion of the surveyed plants: Food (30 percent) and Machinery (20 percent).[9]

Table 5 summarizes the number of available observations for each survey, and the average values for the dependent and explanatory variables used in the estimations. All of these variables are computed using expansion factors.

2.3 Basic Econometric Results

Before discussing the main findings, we summarize previous studies for Chile. There are several empirical analyses of the determinants of firm innovation using different versions of the EIT. Crespi and Katz (1999) and Crespi (1999) have analyzed how industry and plant characteristics may explain differences in innovation using the first version of this survey. Benavente (2005) extends this analysis using three versions of the EIT. Alvarez (2001) and Alvarez and Roberson (2004) focus on trade-related variables as main drivers of innovation activity. There is, however, little evidence on the effects of innovation on productivity in the Chilean case.[10] One exception is the work by Benavente (2006), who applies an approach similar to Crépon, Duguet, and Mairesse (1998). Using the 1998 version of EIT, Benavente (2006) finds that research and

[8] We have carried out four cross-section estimations for each survey. However, the parameters tend to change in sign and significance across surveys making the analysis very hard to interpret.
[9] Appendix 1 provides a brief description of the Chilean manufacturing industry from 1995 to 2005.
[10] For Argentina, see for example, Chudnovsky, López, and Pupato (2006).

innovative activities are positively affected by firm size and market power. Interestingly for this paper, he finds that firm productivity is not affected by innovative results or by research expenditures in the short run.

Table 6 presents the results of the generalized Tobit model for both equations regarding R&D decisions.[11] There is not a significant relationship between international competition and the decision to invest in R&D or in the intensity of R&D. This is an unexpected, especially in a very open economy as Chile. It seems that exports do not contribute to increased R&D efforts in Chile. There are several hypotheses that may explain this result and they deserve further attention in future research. It may be that developing countries specialize in sectors where innovation is not very important for international competition. In that case, export markets are not necessarily an incentive for further investment in R&D. There is evidence for the most export-oriented sectors in the Chilean case that expanding the technological frontier is not a typical feature of successful Chilean industries. Case studies of firms in the wine sector and in agro-industry have shown evidence of this (Moguillanski, Salas, and Cares, 2006).

The effect of low appropriability of the innovation is not statistically significant for both dependent variables, suggesting that imitation is not an important issue in the Chilean context. We also find that using public resources does not affect the intensity of R&D. The demand pull variables are generally associated with higher intensity. Regarding the different sources of innovation, the results are generally not significant, with the exception of universities. In that case, we find that a higher importance of universities as a source of information reduces the intensity of R&D. Finally, in the case of R&D intensity, we find a positive and significant effect of cooperation through formal contracts between firms and universities and/or technological institutes. In terms of plant size, the results suggest that larger firms—especially those with more than 100 workers—are more likely to invest in R&D.

Table 7 shows the results for the estimation of the knowledge production function using process and product innovation as indicators of innovation performance. In general, the predicted value of R&D intensity is positively associated with both indicators, although its statistical significance is lower for product innovation. Two other results are interesting to note. First, we find that lower appropriability reduces process innovation, but does not affect product

[11] All regressions exclude potential outliers. We excluded the top and bottom 1 percent of firms in the distribution of productivity and the top 1 percent in the distribution of R&D intensity. We do not exclude the bottom 1 percent because in the tail of the distribution there are many firms reporting zero expenditure in R&D.

innovation. Second, the relationship between size and innovation is mixed. It is mostly not significant for process innovation, but is positive for product innovation.

Despite the previous results, the main interest of this work is to investigate the effect of innovation on productivity. Table 8 shows the results for the output production function. Column (1) presents results for contemporaneous productivity. The results show that process innovation is positively associated with productivity, but we do not find similar effects with product innovation. However, it can be argued that it takes some time for innovation to affect a firm's productivity. Taking this into account, we estimate the model using leads of labor productivity as a dependent variable. For surveys collected in year t, we estimate the effect of innovation outcomes on productivity one and two years later (t+1, and t+2). The results are shown in columns (2) and (3). In both cases, we fail to find a strong positive relationship between product innovation and productivity, but our findings show a positive impact of process innovation on productivity.

2.4 Robustness Analysis

We carry out several exercises to check the robustness of our results. First, we estimate the Tobit model considering the total expenditure in innovation reported by the firms, not only the investment in R&D. Results for the three equations are shown in Tables 9, 10, and 11. For R&D decisions, we find that most of the variables are not statistically significant, with the exception of size dummies in the decision to invest in R&D. For the knowledge and output production functions, the main results are, in general, unchanged. The positive effect of R&D intensity on the probability of introducing process innovations, and the positive effect of this last variable on productivity are robust to the change in the innovation investment variable.

The second set of robustness results corresponds to the inclusion of two additional variables in the first and the second equations. First, we include a proxy variable for market structure in our R&D regressions. It is usually argued that innovation may be affected by the market share of the firm. As in Crépon, Duguet, and Mairesse (1998) and Benavente (2006), we include this variable (in logs) in the selection and outcome equation of the generalized Tobit model. Second, in the spirit of Acemoglu et al. (2006), we include a variable regarding the firm's distance to the technological frontier. This distance is defined as labor productivity relative to the average of the top 10 percent of the most productive firms in each 3-digit industry. This variable measured in logs is included in the outcome innovation equations.

The results for R&D decisions and the knowledge production function are shown in Tables 12 and 13, respectively. We find that an increase in market share seems to be positive and significantly associated with an increase in the probability of investing in R&D. Regarding R&D intensity, the effect of market share is positive, but not significant. The results for the knowledge production function suggest that distance to frontier negatively affects the probability of introducing product and process innovations, but the effect is only significant for product innovation. This is consistent with Acemoglu et al. (2006), who found that less-efficient firms are less likely to innovate.

The results for productivity in t, t+1, and t+2 are shown in Table 14. Including the two additional variables generates an important change compared to previous results for productivity. As can be seen, the positive effect of process innovation on productivity remains unchanged, but we find now that product innovation also affects productivity positively.

Table 15 summarizes the main (and more interesting) results across different specifications and shows what results are more robust than others. In general, (i) larger plants are more likely to invest in R&D, (ii) R&D intensity increases the probability of process innovation, (iii) R&D intensity does not affect the probability of product innovation, (iv) low apropiability reduces the probability of process innovation, (v) larger firms are more likely to introduce product innovation, and (vi) process innovation increases productivity.

3. Analysis Using Product-Mix Changes Data

This section relies upon information from ENIA's "Formulario Número 3" (F3), taken annually from 1996 to 2003. This data has two main advantages. First, the information on product innovation can be inferred from the data on how plants change their product mix over time. This allows us to obtain an objective measure of innovation rather than a subjective measure as is usually obtained from innovation surveys. Second, the panel dataset allows us to implement a richer methodology to analyze the effect of innovation on productivity.

3.1 Data

The unit of observation in the dataset is a plant with 10 or more employees, and the sample consists of more than 4,000 plants per year from 1996 to 2003, yielding information for almost

35,000 observations. We match the information on plant characteristics with the F3 data on plant products. This allows us to identify the specific goods that the plants produce. It should be noted that more than 95 percent of the plants produce for single-plant firms in 1996, the only year with firm- and plant-level information available.

The definition of a product is specific to the dataset. Available information indicates that it is more disaggregated than a seven-digit Second Revision International Standard Industry Classification (ISIC). Hereafter, "product" or "ENIA product" will refer to the more disaggregated definition. The products can be assigned to different seven-digit and more aggregated ISIC categories: two-digit ISIC categories will be referred to as "sectors" and four-digit ISIC categories will be known as "industries." There are 10 sectors, 95 industries, 264 five-digit ISIC categories, 2,141 seven-digit ISIC categories, and 3,575 ENIA products in the pooled sample. Table 16 presents information on the number of plants and products under alternative product aggregations. Finally, the distribution of products by sector is highly heterogeneous. The number of products by sector ranges from 121 to the 1,296 products produced in the Fabricated Metal Products, Machinery and Equipment sector.[12]

It is also essential to obtain a measure of total factor productivity (hereafter, TFP) for the analysis. TFP is a residual of an estimated production function. We estimate value-added production functions at the two-digit ISIC level following the Levinsohn and Petrin (2003) technique. This leads to the elimination of around 3,000 plant observations for which TFP measures cannot be obtained.[13]

The data on plants' products by year allows us to identify product-mix changes over time and makes it possible to obtain objective measures of product innovation. Those plants that changed their product mix by adding and/or dropping products can be considered innovators. Table 17 presents information on the percentage of plants that introduced different types of changes in their output structure. It shows that almost one-fourth of plants introduced any type of product-mix changes per year and that two-thirds of the changes involved the addition of new products (column Add). The table distinguishes between plants that changed their product mix for the first time (column First) and those that did it by adding products (column First Add). On

[12] For more details on the dataset, see Navarro (2008).
[13] This is the case of plants for which there is missing information on some of the inputs of the production function or plants that are not active for consecutive years.

average, more than three-fourths of the 10.5 percent of the plants that changed products for the first time did so by adding new products.[14]

For the specific purpose of this study, the definition of innovators is restricted to those plants that added products the first time they changed their mix of products (column First Add in Table 17). Since there are plants in the sample that innovated more than once, we want to capture the plants' pre-innovation conditions as clean as possible. As shown in Table 17, we cannot distinguish "product creation" from "product creation for the first time" for 1997. This is because we do not know the history of product-mix changes before 1997. For this reason, we will consider the period 1998-2003 for the analysis.

As a first exploratory exercise leading into the next subsections, Figure 2 shows the evolution of average log TFP among innovators before and after the year they create products in their first product-mix change. That is, we rescaled time so that at time t=0, the first product innovation is introduced. Two preliminary results emerge from Figure 2. First, we observe that plants that innovated experienced drops in TFP during the three years prior to their first innovation. Second, average TFP tends to increase after the first product innovation. Clearly, the main concern arising from Figure 2 is that product innovation may not be endogenous. Thus, we introduce an econometric technique to control for the endogeneity of the innovation decision. In other words, we test whether what is observed in Figure 2 is evidence of a causal effect of innovation on TFP or not.

3.2 Methodology

Even if product entry may be associated with higher TFP levels, it is still not clear from Figure 2 if more productive plants create more products or if product creation leads to productivity increases. It could be that all plants in the sample experience an increase in productivity after the year a particular plant innovated. Indeed, an important problem in the estimation of how innovation may affect productivity is how to deal with this selection problem.

Ideally, one would like to know what would have been the performance of the plants if they had not innovated. Given that the decision to innovate is not random, it is not possible to observe the behavior of the plants that did not innovate because that would incur a selection bias. Instead, we have to create a proper counterfactual of the outcome of innovators conditional on

[14] Note that it could be the case that the first time a plant changes its product mix, it drops a product.

not having innovated. Different techniques can be used to deal with this issue. In our case, we implement the propensity score matching (PSM) method (Rosenbaum and Rubin, 1983) to analyze the impact of innovation on TFP and other outcomes among Chilean plants.[15]

As mentioned before, we define innovators as those plants that added products the first time they changed their mix of products. The treatment is then a dummy variable A_i (add), which takes a value of 1 if the plant introduces a product innovation at any point in time and zero otherwise. The values of A_i determine the assignment of plants to the treatment and control groups. Let $Y^1{}_{is}$ be the outcome of plant i evaluated s periods after treatment. The causal effect of innovation on the outcome after treatment is then $Y^1{}_{is} - Y^0{}_{is}$ where $Y^0{}_{is}$ is the outcome evaluated in case of no innovation ($A_i = 0$). Clearly, $Y^0{}_{is}$ is not observable.

It is standard to define the average effect of innovation on productivity as

$$E\left(Y_{is}{}^1 - Y_{is}{}^0 \middle| A_i = 1\right) = E\left(Y_{is}{}^1 \middle| A_i = 1\right) - E\left(Y_{is}{}^0 \middle| A_i = 1\right).$$

While the first term is observed, the second term is not. An estimator of this counterfactual widely used in the evaluation literature is

$$E\left(Y_{is}{}^0 \middle| A_i = 1\right) = E\left(Y_{is}{}^0 \middle| P(X), A_i = 1\right) = E\left(Y_{is}{}^0 \middle| P(X), A_i = 0\right)$$

where $P(X)$ is the probability of innovation conditional on a set of observable characteristics *X*. Note that the average value of the outcome should be independent of the treatment indicator (conditional independence). We also need to consider a range for $P(X)$ such that the comparison of expected values between the control and treatment groups is feasible (common support).

Accordingly, we first estimate a probit model for the probability of innovation (propensity score) conditional on a set of observables *X*. We need then to find a control group very similar to the treatment group in terms of its predicted probability of innovating p_i . This requires choosing a set *X* of variables that are not influenced by the treatment (Todd, 1999), in other words, characteristics in existence prior to the first innovation. For our study, the elements

[15] There are other studies that used the PSM methodology with plant-level data for manufacturing. De Loecker (2007) studies the impact of starting to export on productivity among Slovenian firms. Serti and Tommassi (2008) do the same for Italian manufacturing firms. Fryges and Wagner (2008) apply a continuous treatment approach to deal with the same question, using German manufacturing data. Gorg, Henry, and Strobl (2008) analyze the effect of government grants on exporting for Irish firms using a multiple treatment propensity score method.

of X should include variables that are thought to affect the probability of introducing a new product the first time a plant innovates. We include in our initial set of observables, lagged TFP, number of products and dummies for exporters, entrants, and years. According to Todd (2008), there is no theoretical basis for how to choose X and the variables included in X can have important implications for the estimator's performance. As a specification (balancing) test, Rosenbaum and Robin (1983) propose choosing a set X such that there are no differences in X between the two groups after conditioning for $P(X)$.

In this study, we apply a balancing test conditioned on the first moments of X following Becker and Ichino (2002).[16] This required reducing the number of variables included in X for the balancing hypothesis to hold. For the estimation of propensity scores for the whole manufacturing sector, X has to include only lagged TFP and year dummies to pass the balancing test. Given that marginal effects on the probit and TFP effects may vary across sectors, we implement this method for each sector (two-digit ISIC category) separately. We then have to choose the appropriate X for each sectoral probit.

Once we have estimated the propensity scores, we match the groups using the method of the nearest neighbor. That is, for each innovating plant with propensity score p_i, a plant j is selected such that its propensity score p_j is as close as possible to p_i. After matching groups of innovating and non-innovating plants, we can finally compute the effect of innovation by comparing the outcomes of the two groups of matched observations. As commonly referred to in the evaluation literature, this is the average treatment on the treated (ATT). This allows us to test the impact of innovation on current TFP and also its leads and lagged values.

To summarize, we estimated propensity scores for the whole manufacturing sector and for each subsector, setting X such that the balancing property holds.[17] We also restricted the analysis to the common support region of propensity scores. A major concern is the validity of the conditional independence assumption in our estimates. This is not testable directly, but as an indirect test we compute the ATT on lagged TFP. Following Heckman and Hotz (1989), a treatment effect on the lagged outcome different from zero would not be consistent with conditional independence. As noted in Table 18, the ATT of innovation on pre-treatment log

[16] The Becker and Ichino (2002) procedure also allows for restricting the analysis to the common support region of propensity scores, as we in fact do in our estimates.
[17] In the estimations, we added the Fabricated Metal Products and Other Manufacturing sectors because of the small number of treatments in the latter.

TFP is nil for all our estimates. This means that there are no differences in TFP between innovators and non-innovators before treatment. Even though it is impossible to be certain about the validity of the conditional independence assumption, the results of Table 18 suggest acceptable progress in reducing the endogeneity of the treatment.

Also related to conditional independence, Blundell and Costa Dias (2000) suggest that a combination of a propensity score matching (PSM) methodology with a differences-in-differences (DID) estimator can improve the quality of an evaluation study. This is because the matching method deals with differences in observables, but cannot control for unobserved differences between the groups. For this reason, the DID estimator is preferred because it removes any time invariant unobserved heterogeneity. Our outcome measures are then TFP levels and the growth of TFP and other outcomes with respect to the time of the first innovation.

3.3 Results

Table 19 presents the ATT of innovation on different outcomes for the whole manufacturing sector, particularly on how innovation affects productivity and its determinants. Row 1 shows the effects on the level of TFP for the year of the innovation $(s = 0)$ and for each of the four subsequent years $(s = 1,2,3)$. We also present data on the number of treated and control observations for each estimation.

Rows 2 to 4 present the growth in TFP, sales, employment, and capital with respect to pre-innovation levels $(s = -1)$ for plants with the minimum number of relevant observations.[18] Results indicate there is no statistically significant effect of innovation on TFP and TFP growth. While the potential qualitative implications of these results are not satisfying, the results do give us confidence with respect to the validity of the technique we used to control for the potential endogeneity of the treatment.

However, we do find a strong effect of innovation on sales growth at the 1 percent confidence level.[19] Plants sales increase on average 7 percent during the year of the first product addition and continue to grow for the next three years. Indeed, four years after the first innovation, sales are 13.1 percent higher for innovators.

[18] For each plant we need a minimum of *s*+2 consecutive observations for the outcome to estimate the relevant ATT in *s*.

[19] Results using valued added instead of sales growth are very similar. We use sales because we believe that this is probably the target variable of plants when deciding to introduce a new product.

These results would seem to be inconsistent with the zero effect found on TFP growth. Note that TFP is computed as a residual from a production function and therefore captures all the unobserved factors affecting value added beyond inputs. If value added, which is highly correlated to sales, increases and TFP does not, we should expect inputs to increase. Indeed, our estimates suggest that the growth in sales after innovation is accompanied by a statistically significant growth in inputs. Indeed, rows 3 and 4 show that employment is 5.5 percent higher and capital stock is 13.8 percent higher four years after the first innovation. This may explain why we do not find any effect of innovation on TFP for manufacturing. Even though innovation causes an increase in sales and inputs, it does not seem to affect productivity.

The above analysis is based on estimates for the whole manufacturing sector and does not consider industry-specific effects. Table 20 presents the effect of innovation on TFP levels for different sectors. Results indicate a positive, immediate effect on TFP for plants in the Food (0.133) and the Textile (0.122) sectors. For the six other sectors, there is no statistically significant effect of innovation on TFP levels. The last two columns of the table show the number of treated and control observations for each estimation. It can be noted that the improved specification of treatment effects gained by estimating effects by sector comes at the expense of smaller numbers of treatments and controls in the estimations.

Table 21 shows the ATT for the growth in TFP with respect to pre-innovation levels by sector. We find an immediate and future impact of innovation on productivity growth for four sectors. These results confirm the previous results for plants in the Food and Textiles sectors, and also indicate future productivity increases after innovation for plants in the Wood and Non Metallic Mineral Products sectors. There is no statistically significant evidence of TFP increases in the other sectors.

Table 22 presents the innovation effects on sales growth by sector. It shows evidence of immediate and future increases in sales in the same four sectors where there is a TFP growth effect and also among plants in the Fabricated Metal Products, Machinery, and Equipment sectors. Also, there is no relevant evidence of changes in sales after innovation for the four other estimations.

Finally, Tables 23 and 24 display the ATT effect of innovation on employment growth and investment. We observe statistically significant increases in employment in the Textile sector immediately after and one year after the first innovation. There is also evidence of future employment increases in plants in the Fabricated Metal Products, Machinery, and Equipment sector, which together with the increase in sales would explain why TFP is not affected by innovation in this sector. Regarding investment, there is a positive and statistically significant effect one year after innovation in the Textile sector (0.132). We also find statistically significant effects on immediate and future investment in the Chemical, Petroleum, and others sectors.

In summary, the sector-specific results provide a better understanding of the effect of innovation on TFP and its determinants. We find that product innovation has positive productivity effects in the Food, Textile, Wood, and Non-Metallic Mineral Products sectors, though the results are statistically significant at the 10 percent level for most of the cases. We do find strong evidence of sale increases after innovation in these sectors, which in some cases is accompanied of input increases.

3.4 Robustness Analysis

Inspired by endogenous growth theory models such as Romer (1990) and Grossman and Helpman (1991), and as a robustness check, we modify the change of mix that defines the treatment. In these models, the firms' productivity is an increasing function of the number of varieties of goods in the market. Adapting this idea to our empirical approach, we define the net addition of products to the firm's total production as an alternative treatment effect. The benefit of this alternative definition is the sound theoretical foundation on which is based. The drawback is that some firms will be continuously net adding products, leading to a permanent "treatment." This case of permanently treated firms casts some doubt on whether our methodology is the most appropriate for dealing with all treated firms.

Table 25, which has the same format as Table 19, presents the ATT of innovation, defined as net additions, on different outcomes for the whole manufacturing sector. The results indicate there is no statistically significant effect of innovation on TFP levels. However, there is a significant effect on TFP growth after two periods. There is also a strong effect on sales growth at the 1 percent confidence level, as well as future effects on employment growth and gross investment one and two years after the treatment, respectively.

Table 26 presents the effect of innovation on TFP levels for different sectors. Results indicate a positive one-year future effect on TFP for plants in the Textile sectors, and a two-year future effect on plants in the Paper, Printing, and Publishing sector. There is no statistically significant effect of innovation on TFP levels for the six other sectors.

Table 27 shows the ATT for the growth in TFP with respect to pre-innovation levels by sector. We find an immediate impact of innovation on productivity growth for the Textile sector and future impact (Years 1 and 2) for the Wood sector. Curiously, there is a negative impact for the Chemical sector one year after the innovation. There is no statistically significant evidence of TFP increases in the other sectors.

Table 28 presents the innovation effects on sales growth by sector. There is evidence of immediate increases in sales in all eight sectors and future increases in seven of them.

Finally, Tables 29 and 30 display the ATT effect of innovation on employment growth and investment. There is a negative impact on employment growth in the Metallic sector, and a positive impact in the Paper sector. On the side of gross investment, there are positive effects in the Non Metallic Mineral Products and Paper sectors, whereas there is a negative effect in the Chemical sector.

4. Conclusions

This paper quantitatively analyzes the effect of innovation activities on productivity among Chilean manufacturing plants using two different sources of information and methodologies. The first approach consists of matching innovation surveys with plant-level data from official surveys for four years (1995, 1998, 2001, and 2005), following Crépon, Duguet, and Mairesse (1998) and Griffith et al. (2006). One striking result is the instability in the empirical relationships through different surveys. Most of the coefficients change sign and significance from one year to another. This finding has interesting implications for other studies using a single survey to analyze the relationship between R&D investment, innovation, and productivity. First, it raises doubts regarding the robustness of the results and the policy implications emanating from a reduced number of cross-section analyses. Second, it suggests that governments need to devote more effort and resources into developing panel data information to deal with heterogeneity more properly and explore changes over time in innovation decisions and productivity.

For these reasons, the analysis focuses on pooled regressions whose results can be interpreted as the average across different surveys. We check the robustness of our results to different specifications. In general, the robust results tend to suggest that: (i) larger plants are more likely to invest in R&D, (ii) R&D intensity increases the probability of process innovation, (iii) R&D intensity does not affect the probability of product innovation, (iv) low appropiability reduces the probability of process innovation, (v) larger firms are more likely to introduce product innovation, and (vi) process innovation increases productivity.

In the second approach, we use matched plant and products data from the official manufacturing survey for 1996–2003 and implement a propensity score matching technique. We analyze the immediate and lagged impact of product innovation on productivity and its determinants. There is no evidence of an effect of innovation on productivity at the manufacturing industry level. However, at the sectoral level, there is a positive impact of innovation on productivity for the Food, Textile, Wood, and Non Metallic Mineral Products sectors. In the robustness exercise, we redefine our treatment effect in light of endogenous growth theories, finding a lagged effect of innovation on productivity at the manufacturing industry level. This effect would materialize two years after an innovation has occurred.

In sum, our evidence suggests the absence of a contemporaneous effect of innovation on productivity. This contrasts with evidence from studies focusing on other countries. However, our results show the presence of lagged effects of product innovation on productivity, materializing two years after the incidence of innovation. Compared with the case of developed countries, this evidence might be consistent with a very slow process of learning by doing in the mastering of new production processes on the part of Chilean firms. These slow and, most of the time uncertain, gains in productivity could help to explain the low levels of investment in R&D activities by Chilean firms.

Appendix 1. Brief Description of Chilean Manufacturing Industry

This Appendix discusses three main aspects of the Chilean manufacturing industry: changes in the industrial structure during the period of study, the evolution of small and medium firms over time, and the productivity slowdown experienced by the manufacturing industry since the Asian crisis.

Appendix Tables 1 and 2 present the share of employment and number of plants across industrial sectors from 1995 to 2005. The evidence suggests that there has not been a significant change in the industrial structure of the Chilean economy during this period. Given that most structural reforms were implemented in previous decades, the industrial adjustment was less severe during the study period (Alvarez and Fuentes, 2006). Food is the most important sector, both in terms of employment and plants, with a share of about 30 percent. This sector experienced a small increase in its relative importance between 1995 and 2005 of approximately 4 percentage points in terms of employment, but not in terms of the number of plants. In contrast, there was a reduction in the importance of some other sectors, such as textiles and apparel, in which the economy has not had a comparative advantage.

To analyze the relative importance of plants of different sizes, all plants are classified in terms of total employment: small (less than 50 workers), medium (more than or equal to 50 workers and less than 200 workers), and large (more than or equal to 200 workers). Appendix Figure 1 shows that the share of small and medium-sized firms in manufacturing employment decreased between 1995 and 2005, from 18 to 16 percent and from 33 to 27 percent, respectively. In contrast, large firms have experienced an increase in employment share from 49 to 58 percent. Appendix Figure 2 shows the importance of each segment in terms of the number of plants. The evidence suggests that these shares have tended to remain constant.

Appendix Figure 3 shows the evolution of productivity (measured as TFP)[20] for the manufacturing industry as a whole. This figure reproduces a similar pattern to aggregate TFP. After several year of strong growth, there was a change in the trend at the end of the 1990s. This coincides approximately with the Asian crisis; since then, the economy and the manufacturing industry have not been able to recover to previous TFP growth rates.

[20] This has been computed by Alvarez and Fuentes (2009) using the Levinsohn and Petrin (2003) methodology to correct for inputs endogeneity.

Appendix Table 1. Manufacturing Industries: Employment Share (Percentage)

ISIC	*Description*	*1995*	*1998*	*2001*	*2005*
311	Food	27%	28%	30%	31%
313	Beverages	3%	4%	4%	4%
321	Textiles	7%	6%	5%	4%
322	Wearing	6%	5%	4%	4%
323	Leather	1%	1%	1%	1%
324	Footwear	3%	2%	2%	2%
331	Wood	7%	7%	8%	9%
332	Furniture	2%	2%	1%	1%
341	Paper	3%	3%	3%	4%
342	Printing & Pub.	4%	4%	4%	3%
351	Industrial chemicals	1%	1%	2%	2%
352	Other chemicals	5%	6%	6%	6%
353	Petroleum refineries	0%	0%	1%	1%
354	Petroleum & coal	0%	0%	0%	0%
355	Rubber	1%	1%	1%	1%
356	Plastic	5%	5%	4%	5%
361	Pottery	1%	1%	0%	0%
362	Glass	1%	1%	1%	1%
369	Other non-metallic	3%	3%	3%	2%
371	Iron & steel	2%	2%	2%	2%
372	Non-ferrous	2%	3%	3%	4%
381	Fabricated metal	8%	8%	7%	8%
382	Machinery	3%	3%	4%	4%
383	Machinery elec.	2%	2%	1%	1%
384	Transport equipment	2%	3%	3%	2%
385	Prof. & scientific eq.	0%	0%	1%	1%

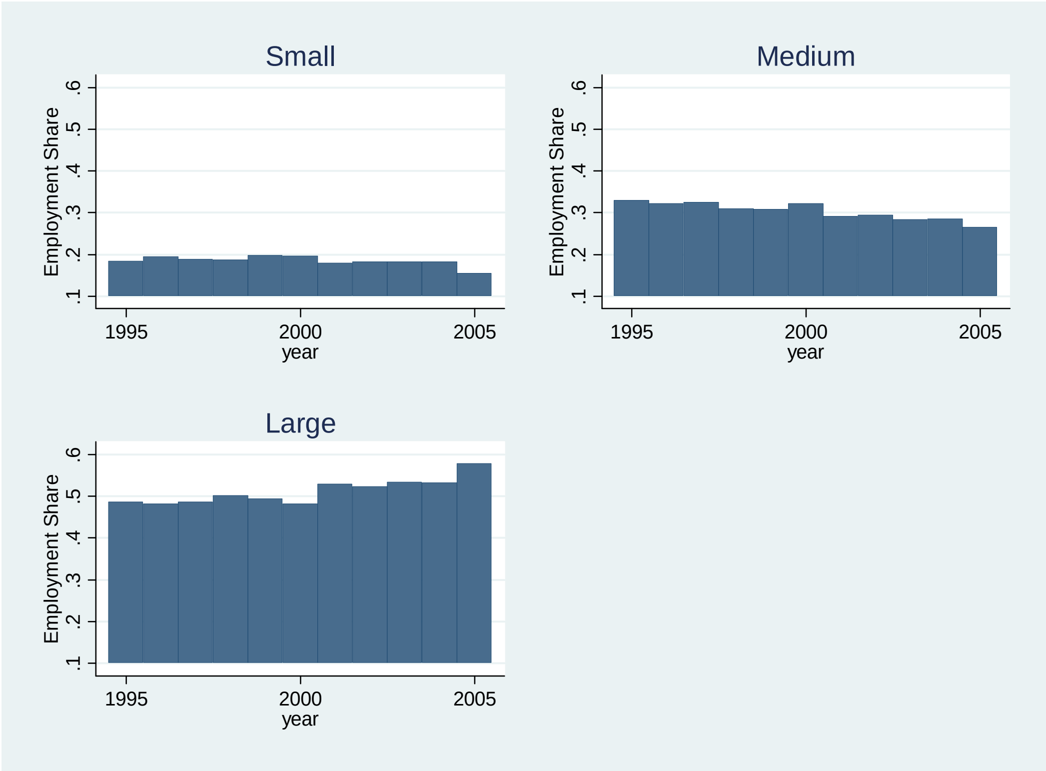
Source: Devised by authors based on ENIA.

Appendix Table 2. Manufacturing Industries: Plants Share (Percentage)

SIC	*Description*	*1995*	*1998*	*2001*	*2005*
311	Food	28%	30%	29%	29%
313	Beverages	2%	2%	2%	4%
321	Textiles	7%	6%	6%	5%
322	Wearing	6%	5%	4%	4%
323	Leather	1%	1%	1%	1%
324	Footwear	3%	3%	2%	1%
331	Wood	8%	7%	7%	7%
332	Furniture	3%	3%	3%	2%
341	Paper	1%	2%	2%	2%
342	Printing & Pub.	4%	4%	4%	5%
351	Industrial chemicals	1%	1%	2%	2%
352	Other chemicals	4%	4%	4%	4%
353	Petroleum refineries	0%	0%	0%	0%
354	Petroleum & coal	0%	0%	0%	0%
355	Rubber	1%	1%	1%	1%
356	Plastic	6%	5%	5%	6%
361	Pottery	0%	0%	0%	0%
362	Glass	0%	0%	1%	1%
369	Other non-metallic	3%	3%	4%	4%
371	Iron & steel	0%	1%	1%	1%
372	Non-ferrous	1%	1%	1%	2%
381	Fabricated metal	9%	10%	9%	9%
382	Machinery	5%	5%	5%	6%
383	Machinery elec.	1%	1%	2%	2%
384	Transport equipment	3%	2%	2%	2%
385	Prof. & scientific eq.	0%	0%	1%	1%

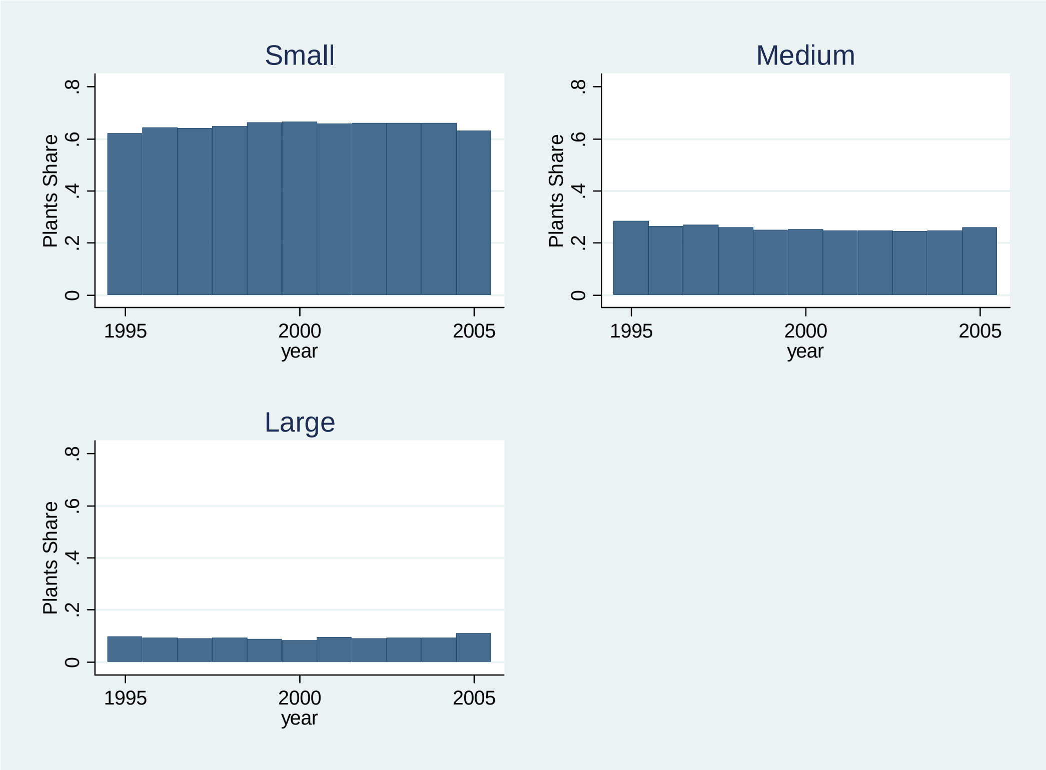
Source: Devised by authors based on ENIA.

Appendix Figure 1. Employment Share by Size



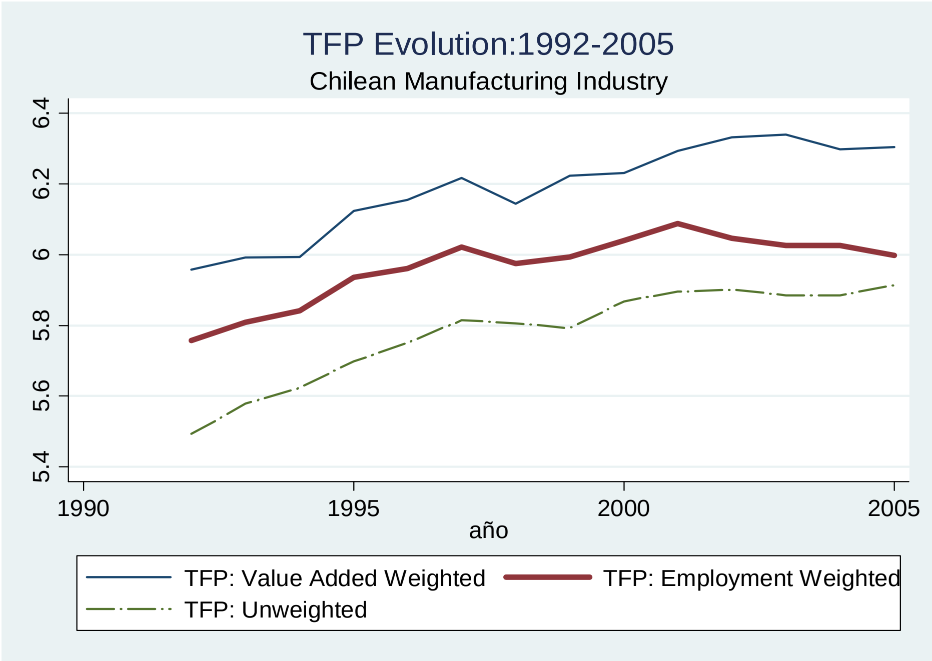
Source: Devised by authors based on ENIA.

Appendix Figure 2. Plants Share by Size



Source: Devised by authors based on ENIA.

Appendix Figure 3.



Source: Alvarez and Fuentes (2009).

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Figure 1. EIT: Firm Distribution across Sectors and Years

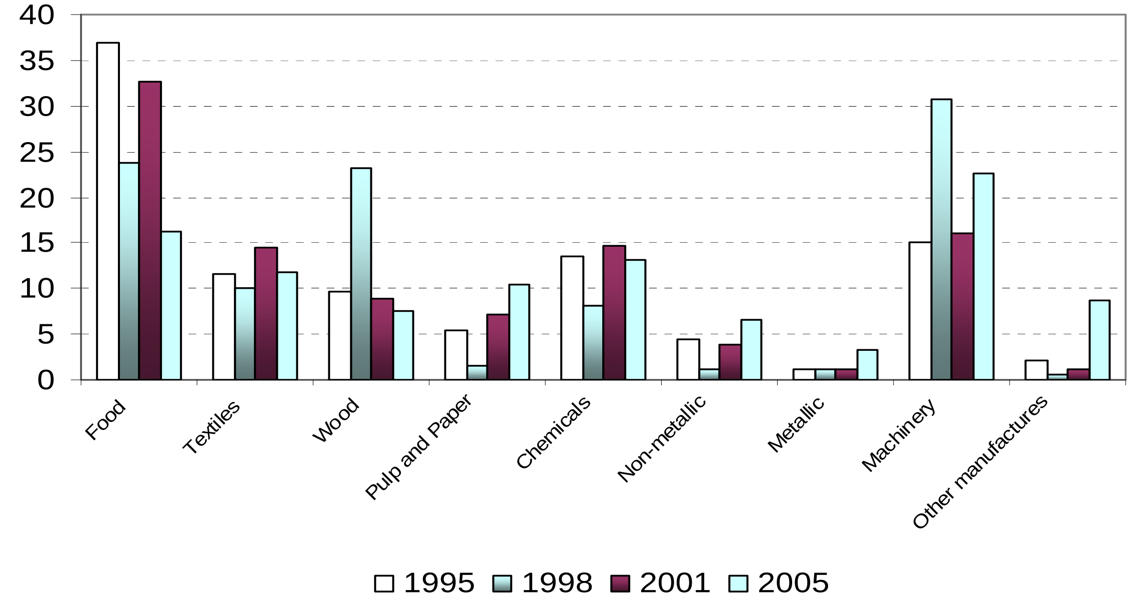
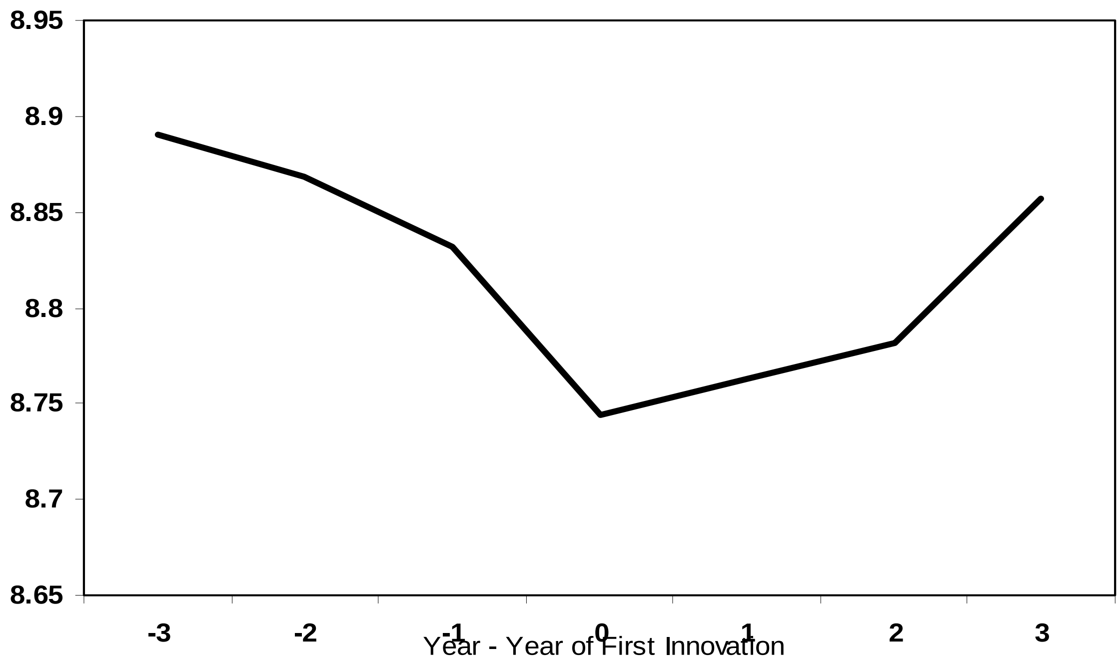


Figure 2. Evolution of Average TFP Before and After the First Innovation



Source: Devised by authors based on ENIA.

Table 1. Annual TFP and Income Per Capita Growth Rates (1960-2000)

	TFP	Income Per Capita
Sub-Saharan Africa	0.48%	0.65%
Scandinavia	0.84%	2.72%
East Asia and Pacific	1.40%	4.20%
Europe and Central Asia (no OECD)	1.94%	3.61%
Middle East and North Africa	0.21%	2.15%
OECD	0.85%	2.70%
South Asia	0.93%	2.28%
Latin America and the Caribbean	0.29%	1.44%
Chile	1.04%	2.39%

Source: Taken from Bravo-Ortega and García (2007), based on Klenow and Rodríguez-Claire (2006) and Penn World Table 6.1.

Table 2. Real Expenditure on R&D as GDP percentage (PPP)

	60-69	70-79	80-89	90-99
Sub-Saharan Africa	0.21%	0.32%	0.53%	0.56%
Scandinavia	1.12%	1.32%	1.92%	2.71%
East Asia and Pacific	0.35%	0.30%	0.67%	0.91%
Europe and Central Asia (no OECD)	.	.	0.64%	0.90%
Middle East and North Africa	0.03%	1.67%	0.28%	1.46%
OECD	2.04%	1.87%	2.25%	2.23%
South Asia	0.23%	0.39%	0.74%	0.64%
Latin America and the Caribbean	0.44%	0.48%	0.36%	0.52%

Source: Devised by authors based on Penn World Table 6.1 Lederman and Saenz (2005), and UNESCO.
Note: (1) Israel is not used for the statistics for the Middle East and North Africa.

Table 3. Expenditure on R&D in Latin America

GDP (%)	*1960-69*	*1970-79*	*1980-89*	*1990-00*
Argentina	0.57%	0.81%	0.40%	0.37%
Brazil	.	0.53%	0.44%	0.84%
Central America and the Caribbean	0.22%	0.27%	0.64%	0.42%
Chile	.	0.32%	0.43%	0.57%
Colombia	.	0.05%	0.11%	0.27%
Mexico	0.17%	0.19%	0.33%	0.33%
Latin America (others)	0.05%	0.35%	0.18%	0.13%
Venezuela	0.09%	0.33%	0.31%	0.39%
Average	0.44%	0.48%	0.36%	0.52%
US$ per capita	1960-69	1970-79	1980-89	1990-00
Argentina	44.4	78.3	37.8	37.4
Brazil	.	28.1	27.4	54.3
Central America and the Caribbean	5.7	12.1	25.6	22.6
Chile	.	16.7	22.6	46.4
Colombia	.	2.0	4.7	14.9
Mexico	8.2	11.5	24.1	25.0
Latin America (others)	2.6	15.8	7.4	6.6
Average	21.5	27.0	20.0	33.3

Source: Devised by authors based on Lederman and Saenz (2005) and Penn World Table 6.1.

Table 4. Number of Patents

US$ per capita	*1963-69*	*1970-79*	*1980-89*	*1990-99*	*2000-04*
Australia	113.7	220.8	339.8	498.4	858.6
China	4.6	6.9	13.9	57.1	260.8
South Korea	1.3	6.8	52.2	1425.6	3802
U.S.	46856.9	46053.1	39359.4	60286.3	86362.2
Israel	39.4	80.4	179.7	450.1	1002.8
Japan	1147.4	5391.4	12240.2	23709.2	34048.6
New Zealand	13.6	25.9	49.6	62.1	129.6
Singapore	0.6	3.0	6.6	64.7	360.0
Latin Am. and the Caribbean	76.7	91.0	86.0	161.7	258.4

Source: Devised by authors based on statistics from USPTO.

Table 5. Data Description EIT
Means of Variables across Surveys

	1995	*1998*	*2001*	*2004*
Innovation Variables				
R&D Intensity	57.34	31.41	37.66	1113.7
Invest in R&D	0.270	0.121	0.175	0.842
Process Innovation	0.491	0.094	0.310	0.348
Product Innovation	0.293	0.140	0.358	0.231
Firm Characteristics				
Labor Productivity	19568	30553	21521	54272
Capital per worker	2488	3008	9880	2963
Competition	0.040	0.145	0.061	0.104
Employment	87.52	74.81	81.50	81.9
Public Support	0.040	0.012	0.092	0.189
Appropriability	0.102	0.043	0.088	0.068
Cooperation	0.149	0.062	0.122	0.016
Market Share	0.007	0.005	0.008	0.009
Investment Intensity	556.8	884.2	965.6	1781.1
Distance to Frontier	1.999	2.418	2.191	2.196
Demand Pull				
Quality High	0.295	0.248	0.332	0.333
Quality Low	0.272	0.202	0.165	0.133
Environment High	0.429	0.435	0.424	0.287
Environment Low	0.298	0.261	0.247	0.152
Sources of Innovation				
Internal firm	0.099	0.014	0.083	0.225
Government	0.001	0.002	0.001	0.041
Internal group	0.001	0.003	0.001	0.205
Universities	0.029	0.007	0.007	0.010
Suppliers & customers	0.058	0.035	0.035	0.028
Competitors	0.027	0.006	0.015	0.013
Observations	525	390	410	823

Source: Devised by authors based on EIT. Nominal variables were deflated using industry-specific deflators.

Table 6. R&D Decisions

	Invest in R&D	*R&D Intensity*
Competition	0.133	0.175
	(0.95)	(0.75)
Cooperation	--	0.346
	--	(2.35)*
Appropiability	0.030	0.247
	(0.25)	(1.06)
Public Resources	--	-0.112
	--	(0.66)
High Quality	--	0.577
	--	(0.35)
Low Quality	--	1.465
	--	(0.91)
High Environment	--	3.571
	--	(3.10)**
Low Environment	--	3.989
	--	(3.55)**
Internal Firm	--	0.251
	--	(1.80)
Government	--	0.288
	--	(1.25)
Internal Group	--	0.214
	--	(1.48)
Universities	--	-0.860
	--	(2.20)*
Suppliers & Customers	--	-0.261
	--	(1.18)
Competitors	--	0.090
	--	(0.21)
Size: 50-99	0.140	--
	(1.49)	--
Size: 100-250	0.477	--
	(6.03)**	--
Size: 250-999	0.599	--
	(7.46)**	--
Size: >1000	0.916	--
	(4.55)**	--
Textiles	-0.438	0.172
	(3.94)**	(0.76)
Wood	-0.460	0.780
	(3.66)**	(2.74)**
Pulp & Paper	-0.302	0.508
	(2.59)**	(2.26)*
Chemicals	-0.160	0.670
	(1.72)	(3.58)**
Non-metallic	0.100	1.103
	(0.67)	(2.31)*
Metallic	-0.187	0.316
	(1.14)	(0.90)
Machinery	-0.279	0.692
	(3.10)**	(3.33)**
Other manufactures	-0.284	1.276
	(1.29)	(3.56)**
Observations	1731	1731
Wald test (rho=0): P-value	0.000	--

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation. Robust z statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 7. Knowledge Production Function

	Process Innovation	*Product Innovation*
R&D Intensity	0.334	0.067
	(5.26)**	(1.10)
Investment Intensity	0.000	
	(0.39)	
Appropiability	-0.200	-0.021
	(3.75)**	(0.44)
High Quality	0.003	0.520
	(0.01)	(1.89)
Low Quality	0.088	-0.643
	(0.27)	(1.97)*
High Environment	-0.321	0.468
	(1.08)	(1.54)
Low Environment	-0.705	0.740
	(2.12)*	(2.22)*
Size: 50-99	0.095	0.088
	(2.39)*	(2.08)*
Size: 100-250	0.008	0.148
	(0.14)	(2.85)**
Size: 250-999	0.038	0.202
	(0.63)	(3.35)**
Size: >1000	0.039	0.275
	(0.40)	(3.14)**
Textiles	0.079	0.129
	(1.16)	(1.93)
Wood	0.024	0.021
	(0.33)	(0.30)
Pulp & Paper	-0.002	-0.008
	(0.04)	(0.16)
Chemicals	-0.082	0.074
	(1.84)	(1.75)
Non-metallic	-0.357	0.185
	(3.26)**	(1.89)
Metallic	-0.137	-0.336
	(1.81)	(4.48)**
Machinery	-0.043	0.066
	(0.80)	(1.28)
Other manufactures	-0.089	0.079
	(0.66)	(0.73)
Observations	1689	1728

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation. Robust z statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 8. Output Production Function

	Productivity (t)	*Productivity (t+1)*	*Productivity (t+2)*
Capital per Worker	0.356	0.431	0.424
	(19.12)**	(17.08)**	(14.70)**
Process Innovation	1.104	0.981	1.586
	(3.36)**	(2.40)*	(3.18)**
Product Innovation	-0.055	-0.108	-0.161
	(0.16)	(0.27)	(0.34)
Size: 50-99	-0.015	-0.121	-0.125
	(0.17)	(1.09)	(0.84)
Size: 100-250	0.007	-0.081	-0.089
	(0.07)	(0.66)	(0.57)
Size: 250-999	-0.163	-0.263	-0.279
	(1.36)	(1.73)	(1.49)
Size: >1000	-0.434	-0.462	-0.451
	(2.57)*	(1.94)	(1.58)
Textiles	-0.366	-0.464	-0.462
	(4.92)**	(4.99)**	(3.65)**
Wood	-0.190	-0.160	-0.189
	(1.97)*	(1.28)	(1.40)
Pulp & Paper	-0.105	-0.080	0.030
	(1.17)	(0.74)	(0.24)
Chemicals	0.067	-0.020	0.062
	(0.98)	(0.27)	(0.65)
Non-metallic	-0.082	-0.104	0.088
	(0.74)	(0.79)	(0.55)
Metallic	0.529	0.104	0.263
	(2.93)**	(0.49)	(1.16)
Machinery	-0.250	-0.257	-0.244
	(3.45)**	(2.86)**	(1.89)
Other manufactures	-0.305	0.064	0.102
	(2.26)*	(0.25)	(0.36)
Constant	7.096	6.800	6.467
	(30.69)**	(25.54)**	(18.25)**
Observations	1520	1090	730
R-squared	0.44	0.49	0.50

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation Robust t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 9. R&D Decisions: Total Investment in Innovation

	Invest in R&D	*R&D Intensity*
Competition	0.115	0.223
	(0.83)	(1.04)
Cooperation		0.210
		(1.45)
Appropiability	0.040	0.108
	(0.33)	(0.47)
Public Resources		-0.193
		(1.13)
High Quality		-1.285
		(0.77)
Low Quality		-0.411
		(0.26)
High Environment		0.094
		(0.08)
Low Environment		0.464
		(0.39)
Internal Firm		0.137
		(0.99)
Government		0.335
		(1.41)
Internal Group		0.163
		(1.12)
Universities		-0.825
		(1.91)
Suppliers & Customers		-0.058
		(0.24)
Competitors		-0.040
		(0.09)
Size: 50-99	0.154	
	(1.64)	
Size: 100-250	0.499	
	(6.22)**	
Size: 250-999	0.604	
	(7.38)**	
Size: >1000	0.869	
	(4.54)**	
Textiles	-0.436	-0.288
	(3.91)**	(1.24)
Wood	-0.460	-0.108
	(3.66)**	(0.37)
Pulp & Paper	-0.303	0.147
	(2.60)**	(0.63)
Chemicals	-0.150	0.578
	(1.61)	(3.23)**
Non-metallic	0.088	0.385
	(0.59)	(0.79)
Metallic	-0.170	0.467
	(1.04)	(1.43)
Machinery	-0.277	0.071
	(3.09)**	(0.35)
Other manufactures	-0.262	0.224
	(1.15)	(0.64)
Observations	1730	1730
Wald test: rho / P-value	0.44 / 0.000	--

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation. Robust z statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 10. Knowledge Production Function

	Process Innovation	*Product Innovation*
R&D Intensity	0.329	0.052
	(3.49)**	(0.57)
Investment Intensity	0.000	
	(0.32)	
Appropiability	-0.154	-0.012
	(3.07)**	(0.26)
High Quality	0.120	0.544
	(0.41)	(1.96)*
Low Quality	0.272	-0.604
	(0.84)	(1.85)
High Environment	0.458	0.631
	(1.76)	(2.36)*
Low Environment	0.075	0.906
	(0.26)	(3.12)**
Size: 50-99	0.143	0.099
	(3.82)**	(2.41)*
Size: 100-250	0.202	0.188
	(6.07)**	(5.37)**
Size: 250-999	0.279	0.252
	(8.30)**	(7.20)**
Size: >1000	0.294	0.325
	(5.10)**	(5.21)**
Textiles	-0.030	0.109
	(0.42)	(1.71)
Wood	-0.037	0.012
	(0.49)	(0.17)
Pulp & Paper	-0.083	-0.021
	(1.49)	(0.40)
Chemicals	-0.130	0.071
	(2.46)*	(1.42)
Non-metallic	-0.246	0.209
	(2.23)*	(2.24)*
Metallic	-0.256	-0.348
	(3.06)**	(4.33)**
Machinery	-0.069	0.064
	(1.24)	(1.23)
Other manufactures	-0.027	0.098
	(0.21)	(0.92)
Observations	1689	1728

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation. Robust z statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 11. Output Production Function

	Productivity (t)	*Productivity (t+1)*	*Productivity (t+2)*
Capital per Worker	0.353	0.428	0.426
	(18.93)**	(17.07)**	(14.65)**
Process Innovation	1.695	1.619	1.705
	(4.24)**	(3.46)**	(2.80)**
Product Innovation	-0.183	-0.321	-0.268
	(0.53)	(0.80)	(0.57)
Size: 50-99	-0.087	-0.201	-0.131
	(0.93)	(1.72)	(0.84)
Size: 100-250	-0.086	-0.173	-0.099
	(0.81)	(1.35)	(0.57)
Size: 250-999	-0.295	-0.395	-0.298
	(2.23)*	(2.48)*	(1.37)
Size: >1000	-0.581	-0.605	-0.440
	(3.18)**	(2.55)*	(1.46)
Textiles	-0.303	-0.403	-0.440
	(3.89)**	(4.25)**	(3.23)**
Wood	-0.150	-0.133	-0.209
	(1.55)	(1.08)	(1.55)
Pulp & Paper	-0.087	-0.085	0.008
	(0.97)	(0.82)	(0.06)
Chemicals	0.086	-0.003	0.054
	(1.26)	(0.04)	(0.58)
Non-metallic	0.013	0.012	0.131
	(0.11)	(0.09)	(0.76)
Metallic	0.525	0.062	0.200
	(2.91)**	(0.30)	(0.89)
Machinery	-0.203	-0.219	-0.247
	(2.74)**	(2.47)*	(1.87)
Other manufactures	-0.254	0.083	0.021
	(1.89)	(0.34)	(0.08)
Constant	6.804	6.515	6.428
	(26.53)**	(22.94)**	(16.55)**
Observations	1520	1090	730
R-squared	0.45	0.49	0.50

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation Robust t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 12. R&D Decisions Including Market Share

	Invest in R&D	*R&D Intensity*
Competition	0.246	0.229
	(1.72)	(0.99)
Cooperation		0.347
		(2.35)*
Appropiability	0.092	0.264
	(0.77)	(1.14)
Public Resources		-0.122
		(0.72)
High Quality		0.401
		(0.24)
Low Quality		1.427
		(0.88)
High Environment		3.632
		(3.15)**
Low Environment		3.957
		(3.51)**
Internal Firm		0.253
		(1.82)
Government		0.294
		(1.28)
Internal Group		0.214
		(1.46)
Universities		-0.861
		(2.21)*
Suppliers & Customers		-0.262
		(1.18)
Competitors		0.092
		(0.22)
Market Share	0.080	0.017
	(6.23)**	(0.44)
Size: 50-99	0.290	
	(2.96)**	
Size: 100-250	0.596	
	(7.34)**	
Size: 250-999	0.674	
	(8.24)**	
Size: >1000	0.918	
	(4.52)**	
Textiles	-0.295	0.243
	(2.55)*	(1.07)
Wood	-0.321	0.852
	(2.48)*	(2.99)**
Pulp & Paper	-0.151	0.596
	(1.24)	(2.67)**
Chemicals	-0.019	0.754
	(0.19)	(4.06)**
Non-metallic	0.260	1.147
	(1.64)	(2.41)*
Metallic	-0.047	0.376
	(0.28)	(1.08)
Machinery	-0.103	0.782
	(1.07)	(3.78)**
Other manufactures	-0.129	1.332
	(0.56)	(3.71)**
Wald test: rho/p-value	0.48/0.00	
Observations	1731	1731

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation. Robust z statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 13. Knowledge Production Function

	Process Innovation	*Product Innovation*
R&D Intensity	0.258	0.054
	(4.82)**	(1.04)
Investment Intensity	0.000	
	(0.29)	
Appropiability	-0.206	-0.020
	(3.83)**	(0.42)
High Quality	0.163	0.588
	(0.58)	(2.13)*
Low Quality	0.151	-0.643
	(0.47)	(1.97)*
High Environment	-0.248	0.432
	(0.86)	(1.46)
Low Environment	-0.580	0.734
	(1.79)	(2.27)*
Dist. Frontier	-0.020	-0.030
	(1.30)	(1.96)*
Size: 50-99	0.018	0.065
	(0.38)	(1.34)
Size: 100-250	-0.056	0.124
	(0.86)	(1.99)*
Size: 250-999	-0.020	0.180
	(0.26)	(2.49)*
Size: >1000	-0.004	0.263
	(0.04)	(2.69)**
Textiles	-0.035	0.090
	(0.50)	(1.38)
Wood	-0.067	-0.003
	(0.89)	(0.04)
Pulp & Paper	-0.107	-0.040
	(1.89)	(0.76)
Chemicals	-0.166	0.049
	(3.26)**	(1.01)
Non-metallic	-0.370	0.174
	(3.34)**	(1.73)
Metallic	-0.200	-0.328
	(2.41)*	(4.13)**
Machinery	-0.150	0.035
	(2.59)**	(0.64)
Other manufactures	-0.132	0.064
	(0.98)	(0.58)
Observations	1689	1728

Source: Authors' estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation. Robust z statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 14. Output Production Function

	Productivity (t)	*Productivity (t+1)*	*Productivity (t+2)*
Capital per Worker	0.299	0.347	0.344
	(16.62)**	(14.04)**	(12.21)**
Process Innovation	2.988	3.498	4.322
	(9.77)**	(9.13)**	(9.06)**
Product Innovation	1.429	1.262	0.925
	(4.34)**	(3.32)**	(2.18)*
Size: 50-99	-0.407	-0.615	-0.628
	(5.05)**	(6.36)**	(4.68)**
Size: 100-250	-0.601	-0.831	-0.866
	(6.92)**	(7.88)**	(6.49)**
Size: 250-999	-1.013	-1.321	-1.352
	(9.63)**	(10.16)**	(8.58)**
Size: >1000	-1.519	-1.930	-1.907
	(9.59)**	(9.14)**	(7.69)**
Textiles	-0.110	-0.034	-0.026
	(1.71)	(0.42)	(0.23)
Wood	0.213	0.290	0.166
	(2.41)*	(2.59)**	(1.38)
Pulp & Paper	0.118	0.274	0.375
	(1.42)	(2.81)**	(3.31)**
Chemicals	0.044	0.075	0.127
	(0.69)	(1.07)	(1.43)
Non-metallic	0.098	0.204	0.484
	(0.84)	(1.41)	(2.98)**
Metallic	1.307	0.989	0.942
	(7.68)**	(4.98)**	(4.55)**
Machinery	0.028	0.136	0.144
	(0.43)	(1.75)	(1.27)
Other manufactures	-0.108	0.449	0.347
	(0.84)	(1.98)*	(1.41)
Constant	5.882	5.450	5.087
	(32.72)**	(27.58)**	(17.70)**
Observations	1520	1090	730
R-squared	0.51	0.56	0.58

Source: Authors'estimations based on ENIA and EIT several years.
Note: Survey year dummy variables were included in the estimation. Robust z statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 15. Summary of Results and Robustness

Basic Model	*Total Investment in Innovation*	*R&D investment + market share and distance to frontier*
R&D decisions		
Cooperation increases R&D Intensity	No	Yes
Larger plants are more likely to invest in R&D	Yes	Yes
Knowledge production function		
R&D Intensity increases the probability of process innovation	Yes	Yes
R&D Intensity does not affect the probability of product innovation	Yes	Yes
Low apropiability reduces the probability of process innovation	Yes	Yes
Larger firms are more likely to introduce product innovation	Yes	Yes
Output production function		
Process innovation increases productivity	Yes	Yes
Product innovation does not affect productivity	Yes	No

Source Authors' summary of results.

Table 16. Data description ENIA Form 3

Year	Plants	Data Products	ISIC 6 digits	ISIC 5 digits
1996	4367	1712	540	244
1997	4138	1663	548	246
1998	3760	1625	536	245
1999	3455	1597	528	239
2000	3394	1688	539	238
2001	3475	1130	416	207
2002	3820	1240	414	206
2003	3879	1289	421	212

Source: Devised by authors based on ENIA.
Note: Matched Plants and products observations after TFP estimations.

Table 17. Percentage of Plants that Changed the Mix of Products

Year	Any	Add	First	First Add
1997	22.6	13.0	22.6	13.0
1998	21.5	14.2	9.5	5.8
1999	25.2	18.5	10.5	8.1
2000	21.4	15.9	6.0	4.4
2001	62.0	53.9	28.4	24.7
2002	26.9	21.1	3.5	2.7
2003	22.2	16.0	5.3	4.0
Average	24.4	18.3	10.5	7.6

Source: Devised by authors based on ENIA.
Notes: Any represents firms that change their product mix change through either adding products, dropping products or both. First are plants that change their product mix for the first time in the sample period. First Add represents plants that added products the first time the changed their product mix. Add represents plants that added products.

Table 18. ATT Effect of Product Innovation on Pre-Treatment TFP

Whole Manufacturing	-0.027
	0.042
Food, Beverages and Tobacco	0.08
	0.077
Textile, Wearing Apparel and Leather	0.034
	0.07
Wood and Wood Products	-0.072
	0.087
Paper, Printing and Publishing	-0.034
	0.083
Chemical, Petroleum, Coal, Rubber, Plastic	-0.01
	0.081
Non-Metallic Mineral Products	-0.132
	0.172
Basic Metal Industries	-0.551
	0.586
Fabricated Metal Products, M&E and Others	-0.033
	0.084

Source: Devised by authors based on ENIA.
Notes: Standard errors in italics. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively

Table 19. ATT of Product Innovation on Different Outcomes in Manufacturing

	S			
	0	1	2	3
Outcome				
1. TFP level	-0.039	0.010	0.014	0.005
	0.046	*0.052*	*0.056*	*0.085*
Number of Treatred	1433	1176	994	418
Number of Controls	1248	1014	845	397
2. TFP growth (s=-1)	-0.010	0.008	0.046	0.094
	0.034	*0.039*	*0.046*	*0.070*
3. Sales growth (s=-1)	0.070***	0.092***	0.134***	0.131***
	0.018	*0.023*	*0.027*	*0.046*
4. Employment growth (s=-1)	0.021*	0.047***	0.034*	0.055*
	0.011	*0.015*	*0.020*	*0.033*
5. Gross Investment (s=-1)	0.025	0.037	0.025	0.138***
	0.028	*0.036*	*0.043*	*0.063*

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). Standard errors in italics. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 20. ATT Effect of Product Innovation on TFP by Sector

	s				s=0	
	0	1	2	3	Treated	Control
Food, Beverages and Tobacco	0.136*	0.108	0.15	0.212	329	1048
Textile, Wearing Apparel and Leather	0.122*	0.121	0.045	0.092	209	579
Wood and Wood Products	0.0240	0.075	0.125	-0.053	192	158
Paper, Printing and Publishing	-0.119	0.055	0.141	0.129	124	1282
Chemical, Petroleum, Coal, Rubber, Plastic	-0.011	-0.001	0.131	0.080	210	177
Non-Metallic Mineral Products	-0.175	0.033	-0.006	0.111	57	669
Basic Metal Industries	0.070	-0.435	-0.140	0.989	40	32
Fabricated Metal Products, M&E and Others	-0.021	-0.026	-0.081	-0.205	328	239

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 21. ATT Effect of Product Innovation on TFP Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.102*	0.038	0.054	-0.075
Textile, Wearing Apparel and Leather	0.074	0.126*	0.072	-0.113
Wood and Wood Products	0.107	0.146*	0.194*	0.020
Paper, Printing and Publishing	-0.070	-0.014	0.134	0.113
Chemical, Petroleum, Coal, Rubber, Plastic	-0.009	-0.032	0.014	-0.025
Non-Metallic Mineral Products	-0.038	0.100	0.178	0.391**
Basic Metal Industries	0.605	-0.226	0.060	0.765
Fabricated Metal Products, M&E and Others	0.001	0.022	-0.027	-0.22

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 22. ATT Effect of Product Innovation on Sales Growth by Sector

	S			
	0	1	2	3
Food, Beverages and Tobacco	0.075**	0.022	-0.01	-0.057
Textile, Wearing Apparel and Leather	0.096**	0.120**	0.132**	0.164
Wood and Wood Products	0.156**	0.158*	0.137	0.063
Paper, Printing and Publishing	0.060	0.086	0.151	0.118
Chemical, Petroleum, Coal, Rubber, Plastic	-0.023	0.092	0.021	0.165
Non-Metallic Mineral Products	0.068	0.150	0.270***	0.138
Basic Metal Industries	0.122	-0.398	-0.272	-0.435
Fabricated Metal Products, M&E and Others	0.083*	0.036	0.078	0.118

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 23. ATT Effect of Product Innovation on Employment Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.032	0.015	-0.056	-0.092
Textile, Wearing Apparel and Leather	0.043*	0.067**	0.057	0.100
Wood and Wood Products	0.008	0.019	-0.008	-0.004
Paper, Printing and Publishing	-0.003	0.017	-0.030	0.009
Chemical, Petroleum, Coal, Rubber, Plastic	0.020	-0.037	-0.142	-0.048
Non-Metallic Mineral Products	0.038	0.104	0.092	0.106
Basic Metal Industries	0.001	0.051	0.033	-0.113
Fabricated Metal Products, M&E and Others	0.021	0.058*	0.057	0.119

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 24. ATT Effect of Product Innovation on Gross Investment by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.039	-0.036	0.048	0.144
Textile, Wearing Apparel and Leather	0.045	0.132*	0.098	0.154
Wood and Wood Products	0.084	0.081	-0.026	-0.172
Paper, Printing and Publishing	0.159	0.160	-0.007	0.049
Chemical, Petroleum, Coal, Rubber, Plastic	0.213***	0.183*	0.080	-0.125
Non-Metallic Mineral Products	-0.013	0.124	-0.174	-0.117
Basic Metal Industries	0.177	-0.045	0.187	0.320
Fabricated Metal Products, M&E and Others	0.117	0.076	0.145	0.046

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 25. ATT of Net Product Additions on Different Outcomes in Manufacturing

	s			
	0	1	2	3
Outcome				
1. TFP level	-0.005	0.049	0.056	0
	0.03	*0.035*	*0.044*	*0.054*
Number of Treatred	1994	1545	1125	837
Number of Controls	12043	8497	5994	4017
2. TFP growth (s=-1)	0.008	0.039	0.075**	-0.014
	0.021	*0.026*	*0.035*	*0.045*
3. Sales growth (s=-1)	0.091***	0.105***	0.097***	0.105***
	0.013	*0.018*	*0.022*	*0.03*
4. Employment growth (s=-1)	0.011	0.042***	0.023	0.028
	0.008	*0.011*	*0.014*	*0.019*
5. Gross Investment (s=-1)	-0.025	-0.003	0.06*	0.054
	0.018	*0.024*	*0.032*	*0.041*

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). Standard errors in italics. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

ATT of Product Innovation on Different Outcomes in Manufacturing

	s			
	0	1	2	3
Outcome				
1. TFP level	-0.005	0.049	0.056	0
	0.03	*0.035*	*0.044*	*0.054*
Number of Treatred	1994	1545	1125	837
Number of Controls	12043	8497	5994	4017
2. TFP growth (s=-1)	0.008	0.039	0.075**	-0.014
	0.021	*0.026*	*0.035*	*0.045*
3. Sales growth (s=-1)	0.091***	0.105***	0.097***	0.105***
	0.013	*0.018*	*0.022*	*0.03*
4. Employment growth (s=-1)	0.011	0.042***	0.023	0.028
	0.008	*0.011*	*0.014*	*0.019*
5. Gross Investment (s=-1)	-0.025	-0.003	0.06*	0.054
	0.018	*0.024*	*0.032*	*0.041*

Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). Standard errors in italics. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 26. ATT Effect of Net Production Additions on TFP by Sector

	s				s=0	
	0	1	2	3	Treated	Control
Food, Beverages and Tobacco	0.06	0.034	0.022	0.016	493	2919
Textile, Wearing Apparel and Leather	0.081	0.128*	-0.067	-0.022	258	940
Wood and Wood Products	-0.005	0.053	0.121	-0.174	261	321
Paper, Printing and Publishing	0.058	0.114	0.229*	0.161	166	147
Chemical, Petroleum, Coal, Rubber, Plastic	-0.066	0.005	0.055	-0.041	282	313
Non-Metallic Mineral Products	0.028	-0.015	-0.162	-0.219	62	499
Basic Metal Industries	0.187	0.506	0.28	-0.921	36	33
Fabricated Metal Products, M&E and Others	-0.052	-0.037	-0.076	-0.135	414	376

Source: Devised by authors based on ENIA.

ATT Effect of Product Innovation on TFP by Sector

	s				s=0	
	0	1	2	3	Treated	Control
Food, Beverages and Tobacco	0.06	0.034	0.022	0.016	493	2919
Textile, Wearing Apparel and Leather	0.081	0.128*	-0.067	-0.022	258	940
Wood and Wood Products	-0.005	0.053	0.121	-0.174	261	321
Paper, Printing and Publishing	0.058	0.114	0.229*	0.161	166	147
Chemical, Petroleum, Coal, Rubber, Plastic	-0.066	0.005	0.055	-0.041	282	313
Non-Metallic Mineral Products	0.028	-0.015	-0.162	-0.219	62	499
Basic Metal Industries	0.187	0.506	0.28	-0.921	36	33
Fabricated Metal Products, M&E and Others	-0.052	-0.037	-0.076	-0.135	414	376

Notes: s refers to periods after first product innovation. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 27. ATT Effect of Net Product Additions on TFP Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.008	-0.036	0.013	0.028
Textile, Wearing Apparel and Leather	0.082*	0.067	-0.103	-0.039
Wood and Wood Products	0.051	0.152**	0.318***	0.156
Paper, Printing and Publishing	0.023	0.033	-0.014	-0.068
Chemical, Petroleum, Coal, Rubber, Plastic	-0.082	-0.136**	-0.01	-0.105
Non-Metallic Mineral Products	0.197	0.17	0.066	-0.055
Basic Metal Industries	0.004	0.678	0.026	-0.547
Fabricated Metal Products, M&E and Others	-0.031	0.065	0.088	-0.019

Source: Devised by authors based on ENIA.

ATT Effect of Product Innovation on TFP Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.008	-0.036	0.013	0.028
Textile, Wearing Apparel and Leather	0.082*	0.067	-0.103	-0.039
Wood and Wood Products	0.051	0.152**	0.318***	0.156
Paper, Printing and Publishing	0.023	0.033	-0.014	-0.068
Chemical, Petroleum, Coal, Rubber, Plastic	-0.082	-0.136**	-0.01	-0.105
Non-Metallic Mineral Products	0.197	0.17	0.066	-0.055
Basic Metal Industries	0.004	0.678	0.026	-0.547
Fabricated Metal Products, M&E and Others	-0.031	0.065	0.088	-0.019

Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 28. ATT Effect of Net Product Additions on Sales Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.085***	0.068**	0.022	0.06
Textile, Wearing Apparel and Leather	0.077**	0.078*	0.017	0.05
Wood and Wood Products	0.141***	0.254***	0.294***	0.259**
Paper, Printing and Publishing	0.085*	0.115*	0.141	0.429**
Chemical, Petroleum, Coal, Rubber, Plastic	0.094**	0.139***	0.046	0.082
Non-Metallic Mineral Products	0.141*	0.26***	0.25**	0.167
Basic Metal Industries	0.426*	-0.218	0.255	0.345
Fabricated Metal Products, M&E and Others	0.071*	0.159***	0.205***	0.228***

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

ATT Effect of Product Innovation on Sales Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.085***	0.068**	0.022	0.06
Textile, Wearing Apparel and Leather	0.077**	0.078*	0.017	0.05
Wood and Wood Products	0.141***	0.254***	0.294***	0.259**
Paper, Printing and Publishing	0.085*	0.115*	0.141	0.429**
Chemical, Petroleum, Coal, Rubber, Plastic	0.094**	0.139***	0.046	0.082
Non-Metallic Mineral Products	0.141*	0.26***	0.25**	0.167
Basic Metal Industries	0.426*	-0.218	0.255	0.345
Fabricated Metal Products, M&E and Others	0.071*	0.159***	0.205***	0.228***

Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 29. ATT Effect of Net Product Additions on Employment Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.016	0.025	-0.001	0.064
Textile, Wearing Apparel and Leather	0.017	0.028	0.055	0.054
Wood and Wood Products	-0.001	0.046	0.017	0.04
Paper, Printing and Publishing	-0.024	0.037	0.005	0.143*
Chemical, Petroleum, Coal, Rubber, Plastic	0.032	0.049	0.029	0.062
Non-Metallic Mineral Products	-0.026	0.055	0.024	0.073
Basic Metal Industries	-0.014	-0.142*	-0.165***	-0.251*
Fabricated Metal Products, M&E and Others	-0.002	0.007	0.013	0.051

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 30. ATT Effect of Net Product Additions on Gross Investment by Sector

ATT Effect of Product Innovation on Employment Growth by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.016	0.025	-0.001	0.064
Textile, Wearing Apparel and Leather	0.017	0.028	0.055	0.054
Wood and Wood Products	-0.001	0.046	0.017	0.04
Paper, Printing and Publishing	-0.024	0.037	0.005	0.143*
Chemical, Petroleum, Coal, Rubber, Plastic	0.032	0.049	0.029	0.062
Non-Metallic Mineral Products	-0.026	0.055	0.024	0.073
Basic Metal Industries	-0.014	-0.142*	-0.165***	-0.251*
Fabricated Metal Products, M&E and Others	-0.002	0.007	0.013	0.051

Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	s			
	0	1	2	3

Food, Beverages and Tobacco	0.036	-0.025	0.096	-0.021
Textile, Wearing Apparel and Leather	-0.029	0.067	0.043	-0.023
Wood and Wood Products	0.016	0.126	0.089	-0.121
Paper, Printing and Publishing	-0.042	0.026	0.13	0.496***
Chemical, Petroleum, Coal, Rubber, Plastic	-0.092*	-0.055	-0.042	0.087
Non-Metallic Mineral Products	0.099	0.262**	0.272*	0.054
Basic Metal Industries	0.149	-0.268	0.211	0.144
Fabricated Metal Products, M&E and Others	-0.078	-0.071	0.001	0.052

Source: Devised by authors based on ENIA.
Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

ATT Effect of Product Innovation on Capital Growth (Gross Investment) by Sector

	s			
	0	1	2	3
Food, Beverages and Tobacco	0.036	-0.025	0.096	-0.021
Textile, Wearing Apparel and Leather	-0.029	0.067	0.043	-0.023
Wood and Wood Products	0.016	0.126	0.089	-0.121
Paper, Printing and Publishing	-0.042	0.026	0.13	0.496***
Chemical, Petroleum, Coal, Rubber, Plastic	-0.092*	-0.055	-0.042	0.087
Non-Metallic Mineral Products	0.099	0.262**	0.272*	0.054
Basic Metal Industries	0.149	-0.268	0.211	0.144
Fabricated Metal Products, M&E and Others	-0.078	-0.071	0.001	0.052

Notes: s refers to periods after first product innovation. All growth rates are with respect to pre-innovation levels (s=-1). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.