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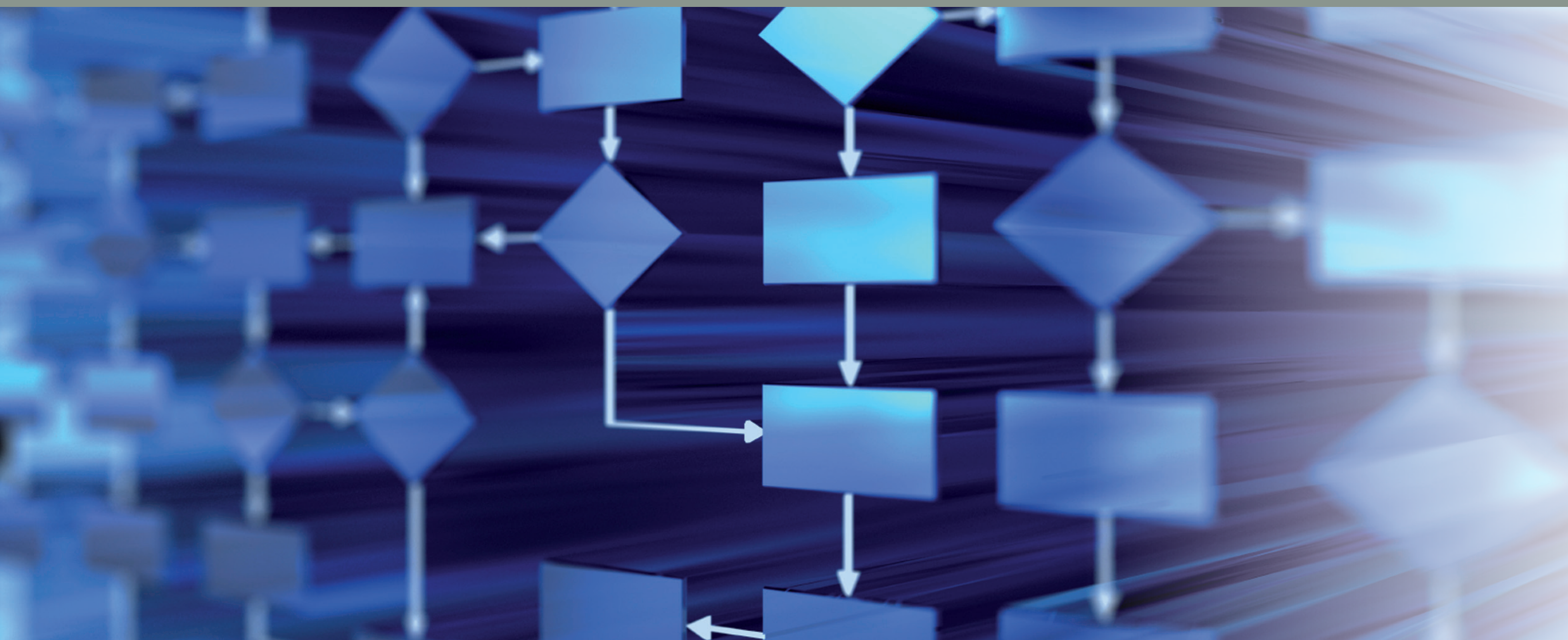

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Intellectual property use in middle income countries: the case of Chile

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Abstract

We analyze the use of intellectual property (IP) by firms in Chile over the decade 1995-2005 as the then middle-income country experienced rapid economic growth of 4.7 percent per year. We use a novel dataset that contains a combination of detailed firm-level information from the annual manufacturing census, information on firms' innovative activities from Chile's innovation surveys, and firms' patent, industrial design, and trademark filings with the Chilean IP office. We use these data to look at how IP use by companies has changed over time and analyze the determinants of IP use, in particular first-time use. We find that sales growth prompts first-time use of patents and trademarks, though such use does not change the growth trajectory of firms nor does it improve their total factor productivity. We also find that trademark use is associated with new-to-the-world product innovation, which suggests that branding may be an important mechanism to appropriate returns to innovation in a middle-income country like Chile.

Keywords: intellectual property, development, Chile

JEL code: O12; O34.

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1. Introduction

There is plenty of evidence on patenting behavior of companies in the industrialized world, above all the U.S. and Europe. There are also studies on the impact of patent systems in developing countries – see Hall (2014) for a survey of this literature. In general, researchers find that stronger patent protection encourages FDI and technology transfer to middle-income economies. However, there is ambiguous evidence on the impact of stronger patent protection on indigenous innovation in developing countries (Branstetter, 2004). The ambiguity arises partly because the impact has been found to vary by development level, with countries at higher levels of development more likely to respond positively to stronger patent protection (Chen and Puttitanun, 2005). These findings direct our attention to more detailed study of the operation of IP systems in middle-income countries and their impact on domestic firms. The present study is a step towards filling this gap by focusing on the use of IP by manufacturing firms in Chile, and the impact of this use on their performance.

A stylized fact supported by the existing literature is that patenting is rare: Balasubramanian and Sivadasan (2011) find that only 5.5% of all manufacturing companies in the U.S. filed a patent between 1977 and 1997. Similarly, Hall et al. (2013) find that only 2.9% of all registered companies in the UK patent, and even among firms engaged in R&D, the share increases only to 4.0%. The evidence also points to substantial differences in the use of patents across economic activities. For example in the UK, 7.7% of manufacturing firms engaged in R&D patent, whereas only 2.6% in business services do so. Although there is no comparable evidence for lower- and middle-income economies, IP registration data for a number of countries – with the exception of China – suggest that domestic companies hold only a small number of patents (Abud et al., 2013).

A small, but growing literature on the use of trademarks finds somewhat higher rates of use.[4] For example, approximately three times as many UK firms hold trademarks as hold patents (Helmers et al. 2011). Trademark registration data for Chile also confirms that the use of trademarks is far more widespread among companies across a large range of industries (Abud et al., 2013). The widespread use of trademarks by firms in developing countries also means that a large share of trademarks is held by domestic as opposed to foreign companies. This stands in stark contrast to the distribution of patent filings, where the vast majority of filings are usually held by foreign companies. In the case of Chile, for example, residents hold about 60% of trademark filings, but only 5-10% of patent filings.

The evidence to date suggests that ownership of patents and trademarks is associated with higher productivity and/or higher firm value, at least in developed economies (e.g., Hall et al., 2005; Greenhalgh and Rogers, 2012; Hall et al., 2013). Balasubramanian and Sivadasan (2011) suggest for the U.S. that the 5.5% of manufacturing firms that patent account for nearly 60% of industry value added and more than 50% of employment. Their findings also indicate that firms grow substantially after they patent for the first time where growth appears to be driven by the sales of new products. In this and in other such studies it is often difficult to tell whether the true association is with the IP right or with the asset that it protects. That is, are the patents and trademarks serving as a (useful) proxy for successful invention by the firm or for the introduction of new products? Or does owning the legal right itself add something to value? The answer to these questions has policy implications, as it tells us to what degree more firms should be encouraged to spend money on securing and enforcing IP rights.

In our analysis, we explore the determinants of the use of IP rights – specifically patents, industrial designs and trademarks – by firms in Chile between 1995 and 2005. We are

[4] For a comprehensive review of the empirical literature on the use of trademarks see Schautschick and Greenhalgh (2016).

particularly interested in first-time use of IP rights: when do firms start using the IP system, what determines that decision, and what is the short and long-term effect of using the IP system on the performance of these companies.

This analysis is possible thanks to a novel, rich data source from Chile that includes production, IP ownership, and innovation data at the firm level. The data were created by collaboration between the Chilean National Institute of Industrial Property (INAPI), the Chilean National Statistical Institute (INE), and the World Intellectual Property Organization (WIPO). INE matched the IP registration data provided by INAPI to 11 annual waves of its manufacturing census (ENIA) and 5 waves of its innovation survey (*Innovacion*). The matched manufacturing census and innovation survey data cover the period 1995-2005 and 1997-2008, respectively. The IP data for all firms is available over the entire 1991-2010 period. The panel structure and the two decades long time series allow us to analyze changes in the use of IP by companies and to relate IP use to company characteristics, innovative activity, and performance. Apart from its broad coverage, the data also stands out because the match of firm-level to IP data was carried out using a unique tax identifier and is therefore not subject to the usual issues associated with name-based matching.

The data cover a particularly interesting period of Chile's recent economic history – a time when Chile experienced rapid economic growth of 4.7 percent a year, which eventually led the country to attain high-income status in 2012. Our results therefore enrich the existing evidence on innovation and firm performance in Chile and more generally in middle-income economies. As such, our analysis offers insights into the effect of IP on the development process and in particular adds to the existing empirical evidence by also looking at IP rights other than patents and manufacturing industries other than pharmaceuticals.

Our earlier work (Abud et al. 2013) established that foreign residents held the vast majority of patents and design rights in Chile during the 1991-2010 period, while Chilean residents held the majority of trademarks. We find a similar but weaker result when we focus on manufacturing firms within Chile: foreign firms hold more patents and design rights than suggested by their numbers (3 percent of the firms), but far fewer trademarks. Patenting is concentrated in a few sectors, notably chemicals and pharmaceuticals, and absent in the electrical and electronics sector, which is characterized by heavy use of patents in high-income countries. Trademarks are used much more uniformly across manufacturing industries in Chile, although they are also most frequently used in pharmaceuticals. Perhaps surprisingly, the determinants of IP use are generally very similar to those found for developed countries, as are the determinants of R&D investment. A notable difference is that foreign firms are in fact less likely to conduct R&D in Chile than domestic companies.

We also find that the use of trademarks depends strongly on new-to-market product innovation and to a limited extent on imitative product innovation by firms in Chile. This suggests that branding strategies may be of some importance for appropriating returns to innovation.

IP use itself does not seem to make any difference in the performance of manufacturing firms. While growing firms are more likely to become first-time users of an IP instrument, such first-time use does not change their growth trajectory, nor does it affect their total factor productivity (TFP). In the case of patents, this finding differs from some of the results for high-income countries (Balasubramanian and Sivadasan, 2011). It may partly reflect the sparse use of patents by Chilean manufacturing firms over time – the vast majority of firms in our sample do not patent, and of those that do, a majority file only a single patent during the 10 years used in our regression analysis. In the case of trademarks, the lack of an independent effect on firm performance is less surprising, given the primary role of the trademark system in removing information asymmetries rather than posing innovation incentives, and there is widespread use of trademarks even among non-innovating firms.

Overall, our results suggest that if the policy objective is to jumpstart innovation-driven growth, policies other than IP protection – such as R&D subsidies and education spending – may initially be more important. Companies start using IP when they are already growing. Even then, the initial focus is on trademarks, which supports the branding of new products and may thus help firms in appropriating returns to innovation. This appropriation mechanism is bound to be of relatively greater importance in middle-income countries than relying on patent exclusivity for inventions that are at the technology frontier. Our results thus point to a sequencing of IP policies, with relatively greater emphasis placed on the trademark system at earlier development stages. The static welfare benefits of the trademark system in preventing consumer confusion and ensuring orderly competition only reinforce this conclusion.

The remainder of this paper is organized as follows. Section 2 describes the data used in our analysis. Section 3 looks at IP use by firms and its impact on their performance based only on the manufacturing survey. Section 4 explores the innovation data and presents the results of estimating a model of R&D, product innovation, trademark use, and productivity, while Section 5 offers a few concluding remarks.

2. Data

The data consists of three components: (1) INE's manufacturing census *ENIA*, (2) INE's innovation survey *Innovacion*, and INAPI's IP data covering patents, industrial designs, utility models and trademarks. In this section we briefly describe these three components and how we combined them into the single dataset used in our analysis. We also provide some short descriptive analysis of the matched dataset.

2.1 Manufacturing survey (ENIA)

The Chilean manufacturing census (ENIA) surveys annually all manufacturing companies with at least 10 employees. ENIA contains detailed plant-level information on inputs and outputs as well as plant characteristics including ISIC (Rev. 3) 3-digit sector codes and geographical location (region). We have access to a total of 11 annual waves of its manufacturing census that cover the period 1995-2005. We focus on this time period in our regression analysis presented in Sections 3 and 4. The ENIA has already been used in a large number of empirical studies, such as Pavcnik (2002), Levinsohn and Petrin (2003), or Fernandes and Paunov (2012).

2.2 Innovation survey (*Innovacion*)

The innovation survey, which is conducted by INE, follows the design of the Community Innovation Survey (CIS). The survey started in 1995 and has been conducted every 3-4 years.

The structure of the survey differs in part substantially across the different rounds. The first three rounds collected data at the plant-level and rounds 4 and 5 collected data at both the firm- and plant-level. The survey has also expanded significantly in its coverage over time. The first two surveys only covered the manufacturing industry, rounds 3 and 4 expanded to mining and utilities (electricity, gas and water), and the subsequent rounds covered firms across all industries. As a consequence, the sample size also increased significantly, from 541 firms in the first round to over 4,200 firms in round 6. We have obtained access to five rounds (rounds 2-6) of the Chilean innovation survey, covering the following periods: 1997-1998, 2000-2001, 2003-2004, 2005-2006, and 2007-2008. The publicly available data does not allow the identification of the same firm across different rounds of the innovation survey. However, for the purposes of our study, INE provided a unique identifier that allows us to identify firms across the different rounds of the survey and to merge the data with the corresponding firms in the ENIA and IP datasets.

One peculiarity of the innovation surveys is that each cover two years, but only the financials (sales, R&D, etc.) are collected separately for both years. All the qualitative variables (innovation, innovation barriers, sources of information, etc.) are asked only once, for the two years of the survey. This means that we use the same values for these variables in the two years when we estimate the empirical models.[5]

2.3 Intellectual property data

The IP data were constructed on the basis of the entire register of patents, industrial designs, utility models and trademarks filed with INAPI over the period 1991-2010.[6,7] The IP data contain bibliographic information as well as information on the prosecution history and legal status of the IP rights. We created a unique, harmonized applicant identifier that allowed us to consolidate the data at the applicant level across the different IP rights and over time. We also attached a unique domestic tax identifier (RUT) to domestic applicants to facilitate the matching with the manufacturing census as well as the innovation surveys.[8] It is important to highlight that the availability of the IP data pre-1995 allows us to identify first-time IP use by the companies in our sample since 1991 when a major reform of the IP system came into effect.[9]

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[5] For comparison, it also means that the innovation variables cover a slightly different period than those collected in the European Community Innovation Survey or the U.S. BRDIS, which generally use three years.

[6] The construction of the IP database is described in more detail in Appendix 2 in Abud et al. (2013). Abud et al. also provide a detailed descriptive analysis of the IP data. Note that under Chilean law, similar to the U.S., industrial designs and utility models are considered as different types of patent rights.

[7] In what follows, we separate patents and industrial designs, and discard the data on utility models, as there are very few of these.

[8] Note that all companies registered in Chile have a RUT; this includes the domestic portion of foreign-owned firms. Hence the data that was combined with ENIA and *Innovacion* includes IP filings by foreign-owned companies registered in Chile.

[9] Chile's Law on Industrial Property (Law 19.039), which covers patents and trademarks, entered into force in October 1991, shortly after the transition from a military dictatorship to democracy. The law introduced important changes to the old Law Decree 958 of 1931. Among others, it introduced product and process patents on food, pharmaceuticals and chemicals (without any pipeline provisions). For more details see Appendix 1 in Abud et al. (2013).

2.4 Combining ENIA, *Innovacion*, and IP data

With the help of the INE, we combined the ENIA, *Innovacion* and IP datasets. The availability of the RUT in our IP data meant that the data could be merged with INE's datasets based on a unique, numeric identifier. Name-based matching was used only to complement the matching procedure and to assess the quality of the match.[10] This represents a major advantage of our data over similar datasets, such as the NBER patent data in the U.S. (Hall et al., 2001) and its extension (Balasubramanian and Sivadasan, 2011) or similar databases for other countries (for the UK: Helmers et al., 2011; or China: Eberhardt et al., 2017). The matched manufacturing census and innovation survey data cover the period 1995-2005 and 1997-2008 respectively. Note that both the ENIA and *Innovacion* data collect data at the plant-level, whereas the IP data are only available at the firm-level. We therefore aggregate the plant-level data to the firm-level (which is uniquely identified by a firm's RUT) to combine the data with our IP data.

Thus the panel structure of our data offers a long time series to analyze changes in the use of IP by companies and to relate IP use to company characteristics, innovative activity, and performance.

2.5 Data description

Table 1 provides an overview of the available data. The table shows that we have on average nearly 5,000 firms in the ENIA between 1995 and 2005, a total of 9,279 unique firms. The number of firms covered by the *Innovacion* data varies much more substantially over time, from 443 for round 2 to 4,243 for round 6. Overall, we have slightly more than 8,000 unique firms in the innovation survey data. The table also shows the number of firms available in both datasets. Nearly 2,000 firms are in both datasets, which is a sizeable number keeping in mind that the ENIA is limited to the manufacturing industry whereas *Innovacion* covers a wider range of sectors from round 3 onward.

Table 1: Overview of data coverage

	ENIA					INNO					Both ENIA and INNO				
Year	*All*	*Patent*	*Design patent*	*Utility model*	*Trade-mark*	*All*	*Patent*	*Design patent*	*Utility model*	*Trade-mark*	*All*	*Patent*	*Design patent*	*Utility model*	*Trade-mark*
1995	4,957	19	15	3	572										
1996	5,275	27	18	6	556										
1997	5,044	22	11	4	551	443	11	5	4	128	418	11	5	3	120
1998	4,785	29	12	7	508	443	15	7	3	120	401	15	7	3	114
1999	4,671	21	13	7	471										
2000	4,544	21	12	3	444	631	8	7	1	118	560	8	7	1	112
2001	4,464	20	17	5	434	631	10	10	5	130	527	9	9	4	118
2002	4,785	24	17	3	452										
2003	4,766	27	16	2	438	2,602	20	10	1	337	1082	14	9	1	168
2004	4,993	31	13	4	461	2,602	27	7	1	356	1067	19	7	1	165
2005	5,034	33	21	3	507	3,194	30	14	2	378	1247	18	13	2	194
2006						3,194	25	9	3	343					
2007						4,243	15	7	2	417					
2008						4,243	20	9	3	391					
Total#	53,318	274	165	47	5,394	22,226	181	85	25	2,718	5,302	94	57	15	991
Unique*	9,279	141	70	36	2,502	8,017	100	45	16	1,524	1,995	52	34	11	480

Total number of firm-year observations.

* Unique number of firms.

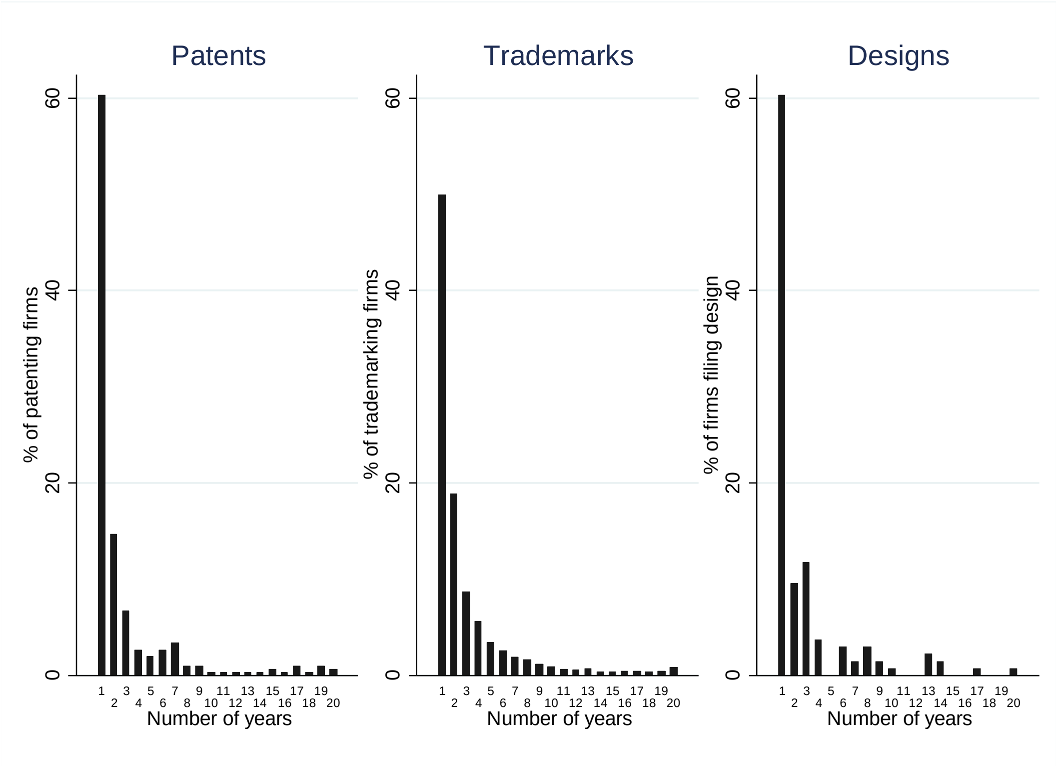
[10] For some Chilean entities in the IP data no (correct) RUT was available. Also, in some cases a firm's RUT can change over time, which makes name-based matching necessary for verification purposes.

Table 1 also shows the results from the match with the IP data.[11] The data show that few firms patent; 141 firms covered by the ENIA have filed for at least one patent between 1995 and 2005 and 100 firms covered by the innovation surveys. If we focus on the firms for which we have data from both ENIA and *Innovacion*, we see that only 52 firms have filed for at least one patent.

Even fewer firms covered by both surveys apply for industrial designs (34) or utility models (11). The number of trademarking firms is much larger: 27% and 19% of firms covered by the ENIA and *Innovacion*, respectively, filed for at least one trademark. Nearly a quarter of the firms covered by both datasets filed for trademarks. These findings are in fact not surprising for two reasons: First, we know from the available evidence on IP use discussed in the introduction that even in developed economies, a very small share of all firms patent. Second, Figure A-1 in the appendix shows the share of patent, design and trademark filings by Chilean applicants among all patent, design and trademark filings by companies over the entire 1991-2010 period (that is, including foreign companies). The figure shows the small share of patents and design rights accounted for by Chilean applicants; in contrast, Chilean companies account for the majority of trademark filings.

Figure 1 shows the share of patenting and trademarking firms that patent in a single or multiple years over the 20-year period 1991-2010. The figure shows that the majority of firms only patent in a single year during the 20-year period, very few companies patent in several and hardly any company every year (6.8% of patenting firms patent in 10 years or more). This indicates that not only very few companies in Chile use the patent system, but even among those that do, most do so only once. A similar pattern applies to design right filings. Although there are also nearly 50% of firms that trademark only in a single year, 50% of trademarking firms file for trademark protection in two or more years during the 1991-2010 period.

Figure 1: Number of years in which firms patent/trademark (1991-2010)



[11] The data refer to applications not grants/registrations throughout the remainder of the paper.

Table B-1 in the appendix shows the number of patent and trademark filings as well as the average number (and standard deviation) of filings by companies in each year for the 1991-2010 period. The table shows that very few firms patent and/or file for design rights. However, some of the firms that patent do file for a substantial number of patents, leading to a very skew distribution. The average number of trademark filings is lower, but with on average 6 filings still large. The large standard deviations for patent and trademark filings in particular, however, suggest highly skewed filing distributions. In other words, a few firms file a large number of patents and trademarks which results in large average patent and trademark counts.

The innovation survey also contains detailed information on the R&D investment of the firms that are covered by the survey. As in the case of patents, relatively few firms report doing R&D of any kind. We provide more information on R&D in Section 4 of this paper.

3. IP use and performance

In this section of the paper we describe the use of patents, designs, and trademarks by Chilean manufacturing companies over the period 1995-2005 and we explore the determinants of IP use, in particular first-time use. We analyze the short and long-term effects of using the IP system on companies' performance, as measured by employment and revenue growth, and TFP.

3.1 Estimation sample

Our sample for estimation initially consists of the 9,279 manufacturing firms (53,318 observations) from the ENIA survey combined with the data on applications for patents, trademarks, and design rights by these firms, all for the years 1995-2005. When defining a firm's IP use status we also made use of IP information for 1991-1994, but these data were not used in estimation owing to lack of other information on the firms during that period. We cleaned the sample by removing observations where the capital stock was equal to zero (~900 observations), materials were missing (~190 observations), employment was missing (7 observations), or the capital-employment, sales-employment or materials-employment ratios changed from the previous year by a factor of more than 20 (~800 observations). We also dropped approximately 1,200 observations on firms that had only one year of data because growth rates could not be computed for these firms. The resulting sample contains 50,216 observations on 7,809 firms, 18 percent of which have gaps in their data of one to three years.[12]

Some simple statistics for these data are shown in Appendix B. Table B-2 shows the sample distribution over time together with some information on IP use. The first panel counts the number of firms in each year who have ever applied for the different types of IP since 1991; that is, the assumption is that once a firm is IP-active, it remains so. The second panel counts only those firms that have made an application in the current year. In both cases, as we indicated above, the dominant IP being used is trademark protection.

Table B-3 shows the industry breakdown we are using in this paper. Some two-digit industries that were sparsely populated have been combined with others (notably tobacco with food, oil refining products with chemicals, and computing machinery and communication equipment with electrical machinery). The majority of firms is in fairly low-tech sectors, with at least a third of the firms in the food and beverage sector, and a large number in apparel, wood products, and fabricated metal products. Most of these sectors are consumer good-intensive, so it is not that surprising that trademarks are much more important than patents for Chilean firms.

The bottom panel of Table B-3 shows the different types of IP use by sector. As before, IP use is dominated by trademarks and this use is widespread across all sectors. In general, sectors that make high use of one kind of IP tend to also use the others (chemicals including pharmaceuticals, rubber and plastics, basic metals, and medical devices and precision instruments). Pharmaceuticals by itself is even more IP-intensive, with 75 per cent of the firms using some form of IP during 1990-2005, and 15 per cent using patents. We also note that fewer than one per cent of the firms ever use utility models and we will therefore not pursue the analysis of this type of IP further.

[12] We annualized the growth rates that were computed across the gaps, and included the observations in our estimations. Dropping these observations makes little difference to the estimates.

3.2 Determinants of IP use

The first step is to analyze the choice of an IP strategy by Chilean firms. We begin by describing the trends in the first IP filing by these firms, and how these vary by industrial sector and other firm characteristics.

Figure 2 shows the breakdown of the various IP filings between domestic and foreign-owned firms in the manufacturing sector. Note that there are about 2,700 patent and 300 design right filings per year in this period in Chile, almost 90 percent of which are from non-residents, while the number of filings from domestic ENIA firms is about 200 patent and 40 design rights per year. In contrast, there are about 29,000 trademark filings per year, less than 15 percent of which are filed by ENIA firms in the manufacturing sector, while domestic firms account for over two-thirds of those.

Figure 2

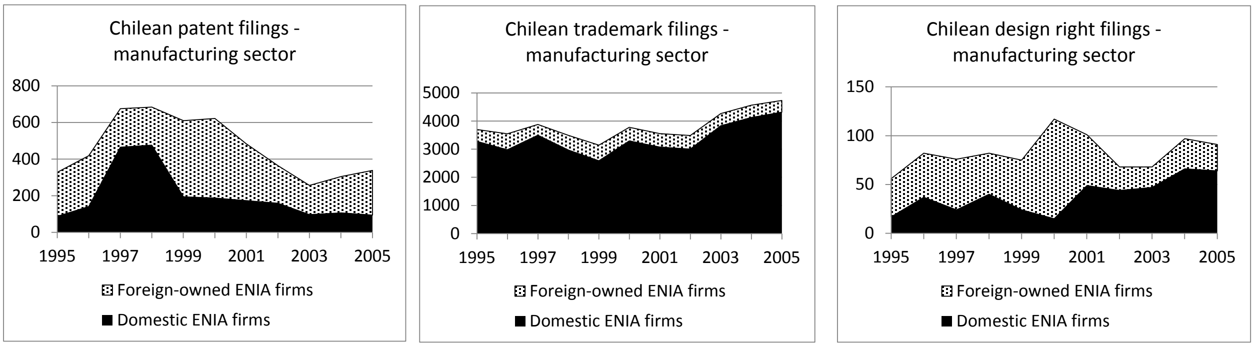


Table 2 shows the use of IP by industrial sectors. We separate them into two groups: those that use IP for the first time in 1995-2005, and those that were already using IP when they entered the sample. The sectors with the largest share of old users are chemicals and related products, metals, and publishing. But these industry variations are not that large. Looking at the new users of IP, the largest increases (by share of firms) are in chemicals and instruments.

Table 2: Use of IP by manufacturing sector

		Number of firms			*Share*		
ISIC2	*Industry*	*No IP*	*Old user*	*New user*	*No IP*	*Old user*	*New user*
15, 16	food products and beverages, tobacco	1,222	293	761	53.7%	12.9%	33.4%
17	textiles	204	53	176	47.1%	12.2%	40.6%
18	wearing apparel; dressing and dyeing of fur	260	57	237	46.9%	10.3%	42.8%
19	leather preparation & goods	123	34	118	44.7%	12.4%	42.9%
20	wood, cork and straw products, ex furniture	342	82	147	59.9%	14.4%	25.7%
21	paper and paper products	89	25	79	46.1%	13.0%	40.9%
22	publishing, printing and media	197	59	112	53.5%	16.0%	30.4%
23, 24	chemicals including coke & refined oil	113	56	207	30.1%	14.9%	55.1%
25	rubber and plastics products	199	81	186	42.7%	17.4%	39.9%
26	other non-metallic mineral products	116	42	104	44.3%	16.0%	39.7%
27	basic metals	55	23	59	40.1%	16.8%	43.1%
28	fabricated metal products	364	87	211	55.0%	13.1%	31.9%
29	machinery and equipment	228	58	136	54.0%	13.7%	32.2%
30, 31, 32	electrical machinery, computing machinery	74	23	54	49.0%	15.2%	35.8%
33	medical, precision & optical instruments	12	6	22	30.0%	15.0%	55.0%
34	motor vehicles, trailers and semi-trailers	59	15	45	49.6%	12.6%	37.8%
35	other transport equipment	31	8	22	50.8%	13.1%	36.1%
36	furniture; manufacturing n.e.c.	231	47	165	52.1%	10.6%	37.2%
	Total	**3,919**	**1,049**	**2,841**			

Our second exploration probes more deeply into the determinants of IP use. Prior literature has identified the following firm characteristics as determinants: firm size, whether it exports, whether it does R&D and how much, ownership status (foreign or domestic, public or private), and the sector in which it operates (Balasubramanian and Sivadasan 2011, Hall et al. 2013, Hall et al. 2014 and references therein). We have the relevant data to explore whether and how these determinants operate in Chile. Later in the paper, we will also include whether a firm has recently introduced a new product, design, or packaging, for the subsample matched to the innovation survey.

Our analysis in this effort is based on descriptive regressions either of the probit (in the case of single indicator for the presence of a patent, design right, or trademark filing) or Poisson (for patent, design, and trademark counts) type. We use the following independent variables:

- Firm size – the log of the number of employees with a contract (more than 90% of employment for most firms).
- Capital intensity – the log of the capital-employment ratio.
- Dummies for foreign and public ownership.[13]
- Dummy for a sole proprietorship.
- Dummy for an exporting firm.
- Dummy for location in the Santiago metro region.
- A set of 18 industry dummies.
- Year dummies.

Simple statistics for all the variables used in the regression below are shown in Appendix Table B-5.

[13] We also included a dummy for mixed foreign and domestic ownership, but it was never significant in any of the models.

Because the manufacturing survey and the IP data are effectively universes of activity in Chile, we can also analyze the impact of the external environment faced by the firm in Chile. This consists both of the competition environment, quantity and nature of competitors and their IP use, and the complete IP environment, including activity by foreign firms. As a first step in this exploration, we computed the market share of each firm in its 4-digit industry, as well as the standard Hirschman-Herfindahl Index (HHI) for the industry and included them in the regressions in log form. Table B-4 in the appendix shows the means of the HHI by our industry classification, as well as the share of 4-digit industries in each industry that are concentrated by the usual definition (HHI>2,500). With the exception of the low-tech sectors textiles, wearing apparel, leather, wood, and paper, the industries appear to be quite concentrated at the 4-digit level. We included the following variables in the regressions:

- Log of the firm's 4-digit industry market share in that year (based on sales).
- Log of the HHI for the firm's 4-digit industry that year (also based on sales).

Table B-4 also shows the average share of sales in each industry that is obtained by foreign-owned firms. The average across all 4-digit industries is about 11 percent, although only 2.8 percent of the observations are foreign-owned, implying that the foreign-owned firms also tend to be bigger than the others. In estimates similar to those in Tables 3-5, we explored whether this share mattered for domestic firm behavior and found that in general the share of foreign-owned sales in the industry did not affect domestic firm IP behavior.[14] The only exception was the number of design rights, which were greater when the share of foreign sales was higher and substantially lower when there were no foreign firms in the industry. This suggests some response to foreign firm behavior, but it is somewhat surprising that there is no patenting or trademarking response to foreign firm sales in the sector.

Table 3 displays a series of probit regressions that model the probability of different types of IP use as a function of these variables. The dependent variable in these regressions is one if the firm had ever applied for a patent, a design right, or a trademark during the year of observation or previous years. Larger firms, exporting firms, and those located in the Santiago metro region are more likely to use any kind of IP protection and the use of trademarks and design rights increases with capital intensity, conditional on size and industry. Surprisingly, although foreign-owned firms are far more likely to patent than domestic firms, they are *less* likely to make use of trademarks. These effects are large when compared to the overall probabilities of patenting and trademarking. For example, the mean trademark probability is 26 percent and being a foreign firm subtracts 10 percent from this number. In this table, the industry impacts are measured relative to the largest manufacturing sector, which is food and beverages. As one might have expected, patenting is more frequent in chemicals, metals and machinery, and motor vehicles, however there is no patenting in the electrical and electronics sector. This reflects the small size of the sector in Chile – representing only one percent of employment in manufacturing – but also suggests that firms in this sector are not on the technology frontier and see no need for protection of this kind. In contrast, trademarks seem to be used more uniformly across sectors, with the highest use in chemicals which includes pharmaceuticals and the lowest in wood products.

[14] Results available from the authors on request.

Table 3

Probability of using IP									
Method of estimation:	*Probit*			*Probit*			*Probit*		
Dependent variable:	*patenting firm*			*trademarking firm*			*has design right(s)*		
Log (employees)	0.0018	0.0005	***	0.0762	0.0067	***	0.0011	0.0005	***
Log (capital/employee)	-0.0002	0.0003		0.0196	0.0033	***	0.0003	0.0002	**
D (foreign ownership)	0.0083	0.0042	***	-0.0977	0.0200	***	0.0013	0.0012	*
D (public ownership)	-0.0008	0.0020		-0.1171	0.0451	**	-0.0007	0.0004	
D (sole proprietorship)	-0.0014	0.0011		0.0342	0.0150	**	0.0008	0.0017	
D (exporter)	0.0013	0.0008	*	0.0474	0.0123	***	0.0006	0.0004	*
D (Santiago metro region)	0.0009	0.0007		0.0445	0.0111	***	0.0009	0.0004	**
Log (market share)	0.0007	0.0003	**	0.0080	0.0042	*	0.0003	0.0002	
Log (4-digit industry HHI)	0.0006	0.0005		0.0295	0.0069	***	0.0004	0.0003	**
textiles	-0.0013	0.0012		-0.0063	0.0241				
wearing apparel; dressing and dyeing of fur	-0.0024	0.0007	*	0.0460	0.0240	**			
leather preparation & goods	-0.0017	0.0010		0.0456	0.0309		0.0028	0.0029	
wood, cork and straw products, ex furniture	0.0031	0.0030		-0.1110	0.0174	***	-0.0011	0.0005	***
paper and paper products	0.0066	0.0056	*	-0.0821	0.0270	***	-0.0007	0.0005	
publishing, printing, recorded media	0.0010	0.0025		-0.0901	0.0219	***	-0.0008	0.0005	
chemicals incl coke & refined oil	0.0167	0.0072	***	0.1234	0.0296	***	0.0004	0.0008	
rubber and plastics products	0.0255	0.0105	***	0.0329	0.0229		0.0098	0.0047	***
other non-metallic mineral products	0.0048	0.0047		-0.0208	0.0275		-0.0009	0.0004	*
basic metals	0.0236	0.0130	***	-0.0202	0.0358		-0.0005	0.0006	
fabricated metal products	0.0052	0.0041	**	-0.0526	0.0185	***	-0.0003	0.0007	
machinery and equipment n.e.c.	0.0026	0.0031		-0.0936	0.0207	***	-0.0010	0.0004	***
electrical and electronic equipment				-0.0325	0.0368		-0.0003	0.0007	
medical, precision & optical instruments	0.0015	0.0049		0.0099	0.0628				
motor vehicles, trailers and semi-trailers	0.0137	0.0124	**	-0.0263	0.0401		-0.0006	0.0005	
other transport equipment				-0.0643	0.0485				
furniture; manufacturing n.e.c.	0.0047	0.0057		-0.0416	0.0222	*	0.0002	0.0010	
Pseudo R-squared	0.286			0.112			0.319		
Chi-squared (df)	464.6 (34)			1538.3 (36)			247.9 (32)		
Number of observations	48,808#			50,216			43,288#		
Share (dep. var.=1)	1.3%			26.1%			0.9%		

Year dummies included; robust standard errors clusterred on firm.

Left out industry is food and beverage products

& DF/dx shown; for dummies change in probability from 0 to 1 is shown.

No patent/design right applications for firms in some sectors, so the observations in that sector are dropped.

Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

Table 4 displays the results of a multinomial logit model for the IP status of a firm: no IP use yet (27,346 observations), first time IP use post-1995 (4,723 observations), and previous IP use before entry into the sample (18,425 observations). The left-out category is no IP use. Both new and old IP users are larger, more capital-intensive, and slightly less likely to be foreign-owned. Exporters and Santiago-based firms are more likely to be IP users, although insignificantly so in the case of new IP use, suggesting earlier adoption of an IP strategy by these firms. However, in general the drivers of IP use are approximately the same for both pre-1995 users and post-1995 users.

Table 4

Probability of using IP

Method of estimation:	*Multinomial logit*					
Dependent variable:	*New IP user*			*Old IP user*		
Log (employees)	0.302	0.053	***	0.346	0.039	***
Log (capital/employee)	0.094	0.023	***	0.118	0.019	***
D (foreign ownership)	-0.373	0.218	*	-0.354	0.163	**
D (public ownership)	-0.114	0.516		-0.354	0.287	
D (sole proprietorship)	0.065	0.110		0.176	0.077	**
D (exporter)	0.146	0.100		0.351	0.067	***
D (Santiago metro region)	0.114	0.085		0.450	0.064	***
Log (market share)	-0.042	0.032		0.030	0.024	
Log (4-digit industry HHI)	0.062	0.055		0.201	0.040	***
textiles	-0.074	0.206		0.021	0.134	
wearing apparel; dressing and dyeing of fur	-0.007	0.188		0.307	0.123	**
leather preparation & goods	0.255	0.235		0.203	0.162	
wood, cork and straw products, ex furniture	-0.287	0.172	*	-0.794	0.139	***
paper and paper products	-0.242	0.270		-0.323	0.194	*
publishing, printing, recorded media	-0.066	0.199		-0.570	0.156	***
chemicals incl coke & refined oil	0.321	0.203		0.304	0.147	**
rubber and plastics products	0.266	0.167		0.148	0.126	
other non-metallic mineral products	0.087	0.217		-0.098	0.165	
basic metals	0.084	0.278		-0.305	0.217	
fabricated metal products	-0.010	0.156		-0.290	0.116	**
machinery and equipment n.e.c.	-0.049	0.199		-0.360	0.150	**
electrical and electronic equipment	0.374	0.297		-0.344	0.237	
medical, precision & optical instruments	0.550	0.509		0.403	0.373	
motor vehicles, trailers and semi-trailers	0.211	0.350		0.089	0.227	
other transport equipment	0.053	0.432		-0.476	0.334	
furniture; manufacturing n.e.c.	-0.208	0.202		0.027	0.130	
Pseudo R-squared	0.079					
Chi-squared (df)	270,518.6 (72)					
Number of observations	50,216					
Share (dep. var.=1)	9.4%			36.5%		

Year dummies included; robust standard errors clusterred on firm.

& DF/dx shown; for dummies change in probability from 0 to 1 is shown.

@ Data for the first year are dropped since there are no new IP users by definition in that year.

Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

Table 5 shows the “intensive margin” regressions focusing on the number of IP applications filed, which are similar to the “extensive margin” regressions in Table 3. Interesting differences are that public firms are more likely to obtain patents but substantially less likely to obtain trademarks, something that was only hinted at in Table 3. Industry effects also change, with almost all industries except chemicals obtaining fewer trademarks than firms in the food and beverage sector.

Table 5

Poisson estimation for number of IP applications in the year

Dependent variable:	*N of patent apps*			*N of trademark apps*			*N of design pat apps*		
Log (employees)	0.787	0.225	***	0.600	0.076	***	0.605	0.187	***
Log (capital/employee)	0.053	0.097		0.073	0.042	*	0.134	0.120	
D (foreign ownership)	4.054	0.519	***	0.408	0.248	*	1.915	0.349	***
D (public ownership)	2.001	0.443	***	-1.089	0.428	**	-1.137	0.947	
D (sole proprietorship)	1.748	1.087		0.141	0.221		-0.692	0.849	
D (exporter)	0.069	0.402		0.213	0.118	*	0.162	0.579	
D (Santiago metro region)	1.462	0.653	**	0.664	0.159	***	1.787	0.526	***
Log (market share)	0.863	0.253	***	0.171	0.047	***	0.515	0.202	**
Log (4-digit industry HHI)	0.306	0.306		0.142	0.073	**	0.432	0.263	*
textiles	-1.872	0.975	*	-0.860	0.203	***			
wearing apparel; dressing and dyeing of fur	-1.378	1.333		-0.593	0.225	***			
leather preparation & goods	-2.574	1.220	**	-0.605	0.236	***	0.747	0.798	
wood, cork and straw products, ex furniture	2.900	0.660	***	-0.701	0.350	**	-2.065	0.710	***
paper and paper products	3.040	0.594	***	-0.748	0.552		1.221	0.751	*
publishing, printing, recorded media	-2.876	0.804	***	-0.797	0.388	**	1.848	0.554	***
chemicals incl coke & refined oil	1.624	0.584	***	0.724	0.228	***	2.012	0.512	***
rubber and plastics products	-1.321	0.823		-0.264	0.240		1.760	0.398	***
other non-metallic mineral products	-1.501	0.932		-0.701	0.242	***	-0.110	0.897	
basic metals	0.719	0.585		-0.789	0.291	***	0.765	1.163	
fabricated metal products	-0.194	0.713		-1.255	0.180	***	0.026	0.705	
machinery and equipment n.e.c.	-1.345	0.860		-1.471	0.252	***	-1.057	0.748	
electrical and electronic equipment				-1.355	0.360	***	1.771	1.139	
medical, precision & optical instruments	-3.218	1.243	***	-1.002	0.403	**			
motor vehicles, trailers and semi-trailers	-1.087	1.426		-0.812	0.418	*	-0.559	0.809	
other transport equipment				-1.102	0.465	**			
furniture; manufacturing n.e.c.	-1.129	0.981		-0.391	0.402		0.142	0.783	
Chi-squared (df)	1502.0 (34)			665.8 (36)			1502.1 (32)		
Number of observations	48,808#			50,216			43,288#		
Number of firms	7597#			7,809			6721#		
Mean dependent var.	0.061			0.541			0.014		

Year dummies included; robust standard errors clusterred on firm.
Left out industry is food and beverage products
No patent/design applications for firms in some sectors, so the observations in that sector are dropped.
Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

3.3 Impact of IP use on performance

IP use can affect the performance of firms in a variety of ways. Patents afford firms exclusive rights over new production processes and new products. In the former case, the inventions contained in patents may directly raise a firm's productivity relative to its competitors. Lower production costs, in turn, may enable the firm to lower prices, increase profit margins and expand sales. New products can in turn attract consumer demand and expand sales; they may also enhance a firm's pricing power, which increases (measured) productivity performance. Trademarks exert a different influence on firm performance. They afford exclusive rights to the brand identity of firms and their products, not the products themselves. Trademarks may relate to innovative products that result from formal R&D, but they may also cover goods and services with little innovative content. Developing successful brand identities – promoted by firms' marketing activities – can attract consumer demand and increase sales. They can also generate price premiums that improve productivity performance. To what extent these forms of IP support these outcomes remains, of course, an empirical question.

To evaluate the impact of IP use on Chilean firms, we compare key indicator variables such as the growth in employment, revenue, and productivity before and after the first use of trademarks or patents by the firm. We drop design rights from this analysis because they are used by fewer than two per cent of the firms.

Because patents and trademarks protect quite different things – brand names versus inventions – we analyze each separately. We use a regression version of a difference-in-differences analysis, which allows us to deal with the unbalanced nature of our panel and the variable timing of the first IP use. The basic model we use is the following:

$$\log y_{it} = \alpha_i + \lambda_t + \beta I\left(IP\,user\right) + \varepsilon_{it} \tag{1}$$

where *i, t* indicate the firm and year, a_i and l_t are firm and year fixed effects, respectively, *I(IP user)* is a dummy variable capturing the first use of trademarks or patents and *y* denotes the outcome variable (employment, sales, or TFP). The coefficient β measures the percentage increase in the dependent variable associated with trademark use for the first time.
TFP is computed as the residual of a regression of log revenue on log employment, log materials, log capital stock, time and industry dummies. Because the dependent variable incorporates both firm-level price and quantity, it captures both the impact of process improvements as well as any ability to raise price due to product improvement and/or branding strategies.

Employment is measured by the average number of employees in the year, both contract and non-contract. If interest is in real productivity, it might be desirable to measure actual person-hours, but these are not available for several of the years in the sample. Alternatively, if interest is centered on the firm's revenue productivity, using the wage bill or payroll plus any social charges would remove any returns going to the firm's employees as a result of productivity improvements. However, payroll information is available for fewer than 20 percent of the observations. Using employee numbers means that any improvements in the skill composition of the labor force will be in the residual TFP.

Capital stock is measured as reported on the ENIA questionnaires, which ask for the nominal value of fixed capital stock. We use beginning of period capital as the input, that is, capital lagged one period, which requires dropping the first year in estimation. There is no information on capital utilization. As in the case of employment, this implies that measured TFP is not "true" productivity, since inputs are included even if they are not actually used in production. However, if using trademarks and the introduction of innovative new or improved products increases the firm's revenues via higher prices or increased demand, an improvement in this measured TFP would be observed, unless these improvements are accompanied by proportionate increases in labor, capital, and materials.

We explored the use of the various estimators that control for unobserved productivity differences across firms, allowing them to evolve as a first order Markov process. These estimators are due to Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015). Using the notation similar to that in those papers, the basic model to be estimated is written as follows:

$$\begin{aligned} \log r_{it} &= \alpha_t + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \\ \omega_{it} &= E[\omega_{it} \mid \omega_{it-1}] + \xi_{it} \end{aligned} \qquad (2)$$

Where *r, k, l,* and *m* denote the logs of revenue, capital stock, labor, and intermediate inputs. ω_{it} is the current productivity level, observed by the firm, while ε_{it} is the unobserved productivity shock. Olley-Pakes (OP) use current investment as a proxy for ω_{it}, arguing that under the assumptions of their model, the choice of investment level is a monotonic function of productivity, conditional on the current level of capital. Unfortunately in our data, about 40 per cent of the observations report zero levels of capital expenditure, so using this proxy is not really appropriate. As Levinsohn and Petrin (2003) and Ackerberg et al. (2015) point out, variations in costs of adjustment can also cause problems for the monotonicity assumption. Nevertheless, for completeness we report results using this estimator, although they are not our preferred results.

The Levinsohn-Petrin (LP) estimator assumes that the level of intermediate inputs is freely chosen by the firm in period *t* in response to its observed productivity ω_{it} and beginning period capital, and uses this fact to construct a proxy for the productivity. Because intermediate inputs are also included in the production function, inducing correlation between the disturbance and the inputs via ξ_{it}, this estimator requires the use of nonlinear instrumental variable estimation rather than nonlinear least squares as in the OP case. The instruments are capital and lagged capital, labor, and intermediate inputs. We found the LP estimates to be the least stable, frequently not converging.

In many settings, the assumption that labor is chosen freely in each period is not defensible, since there can be substantial adjustment costs for labor due to employment protection provisions and the presence of firm-specific human capital. The Ackerberg-Caves-Frazer (ACF) estimator relaxes this assumption by allowing all the inputs to enter the equation for the proxy variable. The downside of this approach is that it requires the firms to face adjustment costs that differ across firms and inputs for successful identification (Bond and Söderbom 2005). In practice, we were successful in estimating this version of the model using the same instruments as those we used for LP.

The estimating equations for TFP are shown in Appendix B, Table B-6. The OLS and ACF estimators are quite similar, whereas OP and LP show somewhat lower capital coefficients and LP an even lower materials coefficient. We prefer the ACF estimates for the reasons discussed and because they require fewer assumptions to be consistent. We also computed TFP estimates industry-by-industry, and these estimates are shown in Table B-7. In practice, all of these TFP estimates were highly correlated (above 0.9), with the exception of the LP estimates, which were correlated about 0.7. This result meant that the choice of TFP estimator ultimately had no impact on our conclusions about the impact of first-time trademark or patent use.

When estimating the difference-in-difference model of equation (1), we treat the observations in the year of first IP use (the zero year) as prior to first-time use because the application can happen any time during the year, and there will presumably be some lag between the IP filing and its impact on the dependent variable.[15] The results of estimation using equation (1) are shown below in Table 6. The top panel is a simple difference-in-differences estimation with firm and year fixed effects plus a dummy for the first-time trademark or patent users after they make their first filing. The first four columns give the results for first-time trademark use, and the second four for first-time patent use.[16]

Although there is clear evidence that firms increase in size after their first trademark application or patent filing, there is no visible increase in their productivity. The bottom panel investigates whether the firms adopting IP strategies are different prior to the adoption from the control firms (firms that have not yet used trademarks or patents). We test this by including two trends: one for all firms and one for the "treated" firms only. The treated firms clearly have a trend growth in employment and sales that is different from the controls, and which knocks out the post-IP coefficient. That is, the first use of trademarks or patents is anticipated by employment and sales growth, but the use of these IP rights does not increase the rate of growth. Note also, that because of the small patenting sample size, which leads to large standard errors on the "treated" variables, it is not possible to conclude that the trademark and patent results are different from each other nor is it possible to rule that out.

[15] Dropping the data for this year instead had little impact on the results.

[16] Table 6 shows results for TFP estimated using the ACF method, for the whole sample and by industry. We also computed these estimates using OLS, OP, and LP estimators and there was no difference in the conclusions, as expected.

Table 6: Impact of first trademark and patent filing

Difference-in-difference estimates

Dep. Variable	Trademark filings# Log E	Log S	TFP	TFP by ind@	Patent filings# Log E	Log S	TFP	TFP by ind@
D (after first tm/patent)	0.037*	0.157***	-0.019	-0.014	0.070	0.268***	0.005	0.023
Robust s.e.	(0.015)	(0.021)	(0.011)	(0.011)	(0.055)	(0.051)	(0.032)	(0.034)
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.032	0.034	0.195	0.034	0.029	0.028	0.058	0.035
Standard error	0.264	0.354	0.237	0.234	0.272	0.356	0.238	0.233

Difference-in-difference estimates with trends

Dep. Variable	Trademark filings# Log E	Log S	TFP	TFP by ind@	Patent filings# Log E	Log S	TFP	TFP by ind@
D (after first tm/patent)	0.006	-0.002	-0.018	-0.007	-0.030	-0.098	0.028	0.026
Robust s.e.	(0.016)	(0.020)	(0.013)	(0.013)	(0.053)	(0.056)	(0.040)	(0.039)
Trend	-0.020***	0.021***	-0.046***	-0.005***	-0.014***	0.029***	-0.017***	-0.006***
Robust s.e.	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Relative treated trend	0.015***	0.019***	0.001	0.000	0.026*	0.053***	-0.004	0.000
Robust s.e.	(0.004)	(0.004)	(0.003)	(0.003)	(0.011)	(0.013)	(0.008)	(0.007)
Year dummies	no	no	no	no	no	no	no	no
R-squared	0.027	0.042	0.175	0.003	0.017	0.049	0.026	0.004
Standard error	0.265	0.352	0.240	0.238	0.274	0.352	0.242	0.237
Observations (firms)		26,133 (4,964)				40,558 (7,965)		
Number of first-timers		1,045				128		
Number of prior users%		2,813				45		

Columns 1, 2, 5, and 6 are fixed firm effect estimation with standard errors clustered on firm. Columns 3, 4, 7, and 8, use ACF estimates for TFI

@ TFP estimated by industry using ACF estimator. Industries 17 (textiles) and 35 (other transport equipment) excluded.

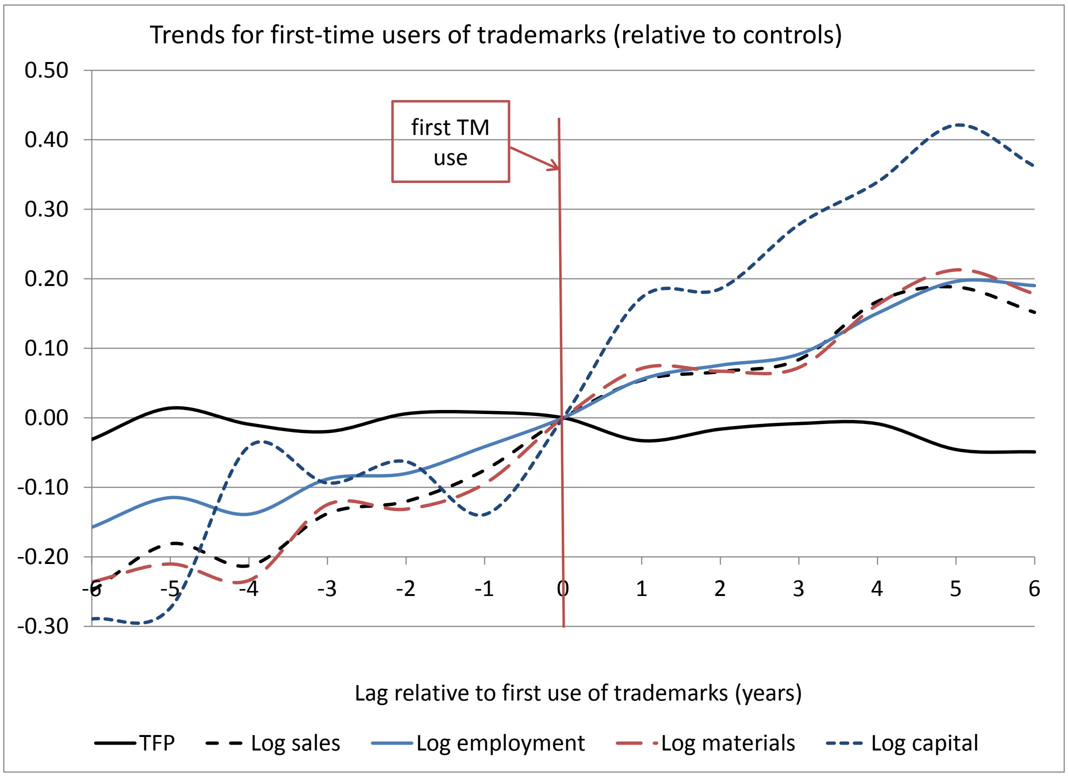
Columns 1 to 4 exclude firms that always use trademarks; Columns 5 to 8 exclude firms that always use patents.

% These firms are not in the estimation sample.

Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

The result for trademarks is shown graphically in Figure 3, which is based on a within firm regression that includes year dummies along with a complete set of separate dummies for the lag between the observed year and the year of first trademark use. The figure shows the relative trend (growth rates) of TFP and its inputs around the time of first trademark use. It is fairly apparent that firms adopting trademarks are growing firms, and that trademark use does not change their trajectory. Sales and materials inputs track fairly closely, while employment grows smoothly and somewhat more slowly. Fixed capital follows the same pattern, but with more fluctuation, and with a jump around the time of first trademark use. Because all of the input variables grow in parallel with output, there is little visible impact on the average firm's productivity from first time trademark use.

Figure 3



At face value, these findings suggest that firms experiencing sales growth at some point turn to the IP system in their commercial strategy. However, first-time IP use does not seem to change the growth trajectory, nor does it improve measured TFP. In the case of trademarks, the absence of a productivity response is less surprising, given the primary objective of the trademark system to reduce information asymmetries rather than to incentivize innovation, and the widespread use of trademarks even among non-innovating firms. In the case of patents, the prior literature for developed countries shows mixed results: Hall et al. (2013) and Hall and Sena (2017) found no or only a weak productivity response for the UK, while Balasubramanian and Sivadasan (2011) did find a response for the U.S. Chappell and Jaffe (2018) report a similar result for New Zealand firms, finding that intangible investment is associated with higher revenue, capital, and labor, but not with higher productivity. In the present analysis, it is worth recalling the small number of Chilean manufacturing firms using patents, which limits statistical inference. In addition, most firms only apply for a single patent during the sample period (see Figure 1), which questions the analysis' premise that first-time patent use captures a more durable embrace of the patent system. These factors may well explain the absence of a productivity response to patenting in the Chilean context.

4. Innovation, trademarks, and productivity

Tables B-1 and B-2 in the appendix make it clear that the number of firms using trademarks dwarfs the number using patents or design rights, by a factor of about 20 times. Therefore we focus on trademarks in this section of the paper, where we further explore the relationship between innovation, the use of trademarks, and productivity using data from the two surveys (ENIA and *Innovacion*) and the trademark data. Note that the innovation surveys are available only for seven years between 1997 and 2005, so the period of analysis is somewhat shorter than in the preceding section. In addition, as Table 1 showed, the sample will involve far fewer observations. After cleaning, we have 5,126 observations on 1,976 firms, 2.6 years per firm on average.

Table 7 shows the types of innovation surveyed, and their frequency in our sample, for all firms and for the R&D-doing firms only. 52 percent of manufacturing firms in Chile report either a product or process innovation during the past two years. For comparison, the number for U.S. manufacturing is 32 percent during 2012-14 (U.S. National Science Board 2018). The frequency of product and process innovation of all kinds is also somewhat higher than observed by Hall and Sena (2017) for the UK, although their sample is not comparable as it included non-manufacturing firms. When the sample is restricted to R&D-doing firms, almost all the firms have some form of product or process innovation during the period, balanced fairly equally between the two types.

Table 7

Innovative activity and trademarks

	All firms		*R&D-doers only*	
Type of innovation	*Number innovating*	*Share with trademarks*	*Number innovating*	*Share with trademarks*
Management innovation	2,083	36.9%	1055	42.7%
Organizational innovation	1,985	33.4%	1022	41.3%
Design innovation	1,585	49.0%	880	50.8%
Packaging innovation	980	45.1%	587	51.1%
Any process innovation	2,191	38.5%	1167	43.9%
Process new to market	1,167	64.6%	744	45.6%
Process new to firm	1,990	25.0%	1038	43.4%
Process new to firm, not to mkt	1,024	33.7%	423	40.9%
Any product innovation	2,072	40.4%	1169	45.2%
Product new to market	1,308	54.9%	835	54.0%
Product new to firm	1,806	32.2%	1011	39.6%
Product new to firm, not to mkt	764	33.4%	334	38.3%
Any product or process innovation	2,658	37.4%	1371	43.4%
Observations	5,126	28.5%	1,536	42.1%

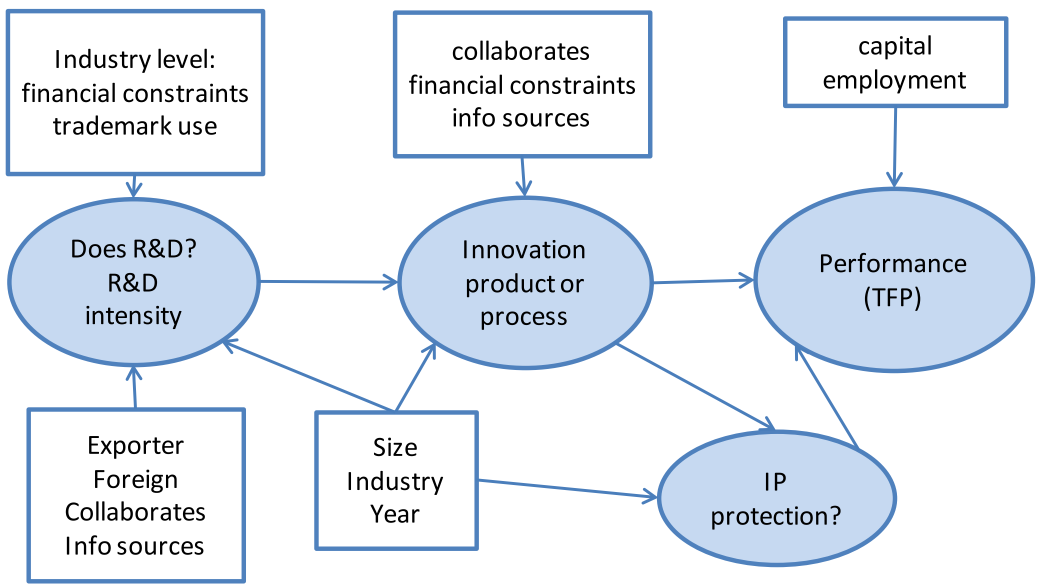
Our subsequent analysis will focus on product innovation, which is likely to be the most associated with trademark use. However we note in passing that 28 out of the 34 firms that own design rights also report that they innovated some kind of design, although the remaining 645 design innovators did not use the design right system. Similarly, firms with packaging innovations are more likely to hold either or both of a design right or trademark than other firms, but most of them do not.

4.1 CDM model

In order to jointly analyze R&D, product innovation, trademark use, and productivity outcomes for the sample, we use the well-known model of Crepon, Duguet, and Mairesse (CDM) (1987). This model was designed to deal with the type of data we have here: essentially repeated cross sections with a very sparse time dimension, firms without reported R&D that innovate, and several qualitative variables. Hall and Sena (2017) extended the model to include IP; we use a variation of the model here. The basic model has three parts: 1) equations for R&D; 2) equations for the innovation outcome(s) and the choice to protect via IP (in this case, trademarks); and 3) a conventional productivity equation that also depends on innovation and trademarks. Figure 4 shows the structure of the model. The squares contain the predetermined variables in the model and the ovals are the key endogenous variables.

Figure 4

The R&D-innovation-IP-performance model



This model schematic is implemented by a set of estimation equations described below. The index *i* denotes a firm, *j* the two-digit industry of the firm, and *t* the time period.

The R&D model uses a two equation sample selection (Heckman) model for the presence of R&D and its intensity to predict R&D intensity for all observations, not just those with observed R&D. This predicted R&D is then included as a regressor in the innovation and IP equations, effectively a form of instrumental variable estimation.

$$rd_{it} = \begin{cases} 1 \; if \; rd_{it}^{*} = w_{it}\alpha_1 + \widetilde{w}_{jt}\alpha_2 + d_j + d_t + \varepsilon_{it} > 0 \\ 0 \; if \; rd_{it}^{*} = w_{it}\alpha_1 + \widetilde{w}_{jt}\alpha_2 + d_j + d_t + \varepsilon_{it} \le 0 \end{cases} \quad (2)$$

$$r_{it} = \begin{cases} z_{it}\beta_1 + \tilde{z}_{jt}\beta_2 + \tilde{d}_j + \tilde{d}_t + e_{it} \; if \; rd_{it} = 1 \\ 0 \qquad\qquad\qquad\qquad\qquad\quad if \; rd_{it} = 0 \end{cases}$$

$$\begin{pmatrix}\varepsilon_{it}\\ e_{it}\end{pmatrix} \sim N\begin{pmatrix}1 & \\ \rho\sigma & \sigma^2\end{pmatrix}$$

where *rd* is a dummy variable for reported R&D, *r* is the observed R&D intensity, measured as spending per employee, and *w, z*, $\tilde{w}$, and $\tilde{z}$ are a set of predetermined variables describing the firm and industry (the variables with a tilda). The d_j and d_t are industry and time dummies.

These two equations are estimated jointly by maximum likelihood, and then the expected R&D intensity is computed, conditional on whether or not actual R&D was observed.

The third equation is the innovation equation. Innovation is an indicator variable, so the equation is estimated using a probit model. We estimate two versions of the innovation equation: one that includes the expected (predicted) R&D intensity on the right hand side, and one that includes observed R&D intensity. In the latter case, we also include a dummy variable equal to one when R&D is not observed. In the equation below, *r* denotes the R&D variable(s), and x^1 the other included control variables.

$$INN_{it} \sim \gamma_1 r_{it} + x_{it}^1 \delta_1 + d_j + d_t + u_{it}^1 \tag{3}$$

The fourth equation is an equation for trademark use, specified in a similar manner, and estimated using probit with the two different choices for R&D:

$$TM_{it} = \gamma_2 r_{it} + x_{it}^2 \delta_2 + d_j + d_t + u_{it}^2 \tag{4}$$

We model productivity as in section 3.3, adding information on innovation and the use of trademarks to the regression. The model we use is otherwise conventional:

$$y_{it} = \alpha e_{it} + \beta c_{it} + \gamma m_{it} + \delta_0 TM_{it} + \delta_1 INN_{it} + \delta_2 TM_{it} \times INN_{it} + \lambda_t + \theta_j + \varepsilon_{it} \tag{5}$$

y, e, c, and *m* are the logs of sales, employment, capital, and materials respectively. TM and INN correspond to the various trademark and innovation variables. This equation is estimated by OLS and the standard error estimates are clustered at the firm level, which allows free correlation across time.

4.2 R&D equation

The R&D portion of the model is based on the idea that many firms that do not report R&D to the survey may actually undertake informal R&D, even if they do not track it separately. Table B-8 in the appendix shows the distribution across industries of the number of firms that do R&D continuously and those that do it only occasionally. The overall shares are roughly equal, at 16 percent, so 32 percent of the firms in our ENIA-*Innovacion* sample report doing R&D at some point. The fact that this share is relatively low compared to the U.S. and Europe suggests that the CDM assumption that some manufacturing firms are doing informal R&D and not reporting it may not be warranted in a country like Chile. Nevertheless, in what follows we do find that R&D predicted from the model does have a substantial impact on innovation.

We include the following variables in both of the R&D equations: firm size and industry, whether the ownership is foreign, whether the firm exports or collaborates, and whether the firm uses internal and/or external sources for information about innovation. We also include some industry level variables for the degree of financial constraints faced by firms in the industry, and the extent to which the industry uses trademarks.[17]

The results of estimating this model using maximum likelihood with robust standard errors clustered on the firm are shown in Table 8. The estimated correlation of the disturbances in the two models is positive and similar to that obtained by Hall and Sena (2017) for the UK. Choosing to invest in formal R&D (30 percent of the observations) is dependent positively on firm size, whether it exports, whether it collaborates with others, its (domestic) market share in the 4-digit industry, and on the use of internal (to the group to which it belongs), university, and public institution information sources. Foreign-owned firms are much less likely to invest in R&D, at least in Chile. There is no role for the industry variables, which may reflect the fact that much of what is not explained by industry and year is due to noise, since both variables are based on qualitative discrete variables. The R&D intensity equation has similar results except for firm size, where intensity falls with employment. Some of this effect is doubtless due to measurement error in employment, which will induce negative correlation between the dependent variable and the log of employment, and some is due to the strong correlation of firm size with market share.

Table 8

R&D equations

	Invests in R&D (0/1)			*Log (R&D/employee)*		
Dependent variable	*Coeff.*	*s.e.*		*Coeff.*	*s.e.*	
Log (employment)	0.152	0.036	***	-0.683	0.077	***
D (foreign owner)	-0.278	0.103	***	-0.288	0.201	
D (exporter)	0.213	0.066	***	0.268	0.154	*
D (collaborates)	0.639	0.102	***	0.739	0.188	***
Log market share in 4-digit ind.	0.061	0.024	**	0.244	0.055	***
Log HHI of 4-digit industry	0.007	0.050		0.009	0.104	
Industry financial constraints	0.185	0.118		-0.082	0.235	
Industry trademark use	0.178	0.107	*	0.265	0.225	
D (internal innov info sources)	0.756	0.060	***	0.324	0.135	**
D (customer info sources)	-0.034	0.107		-0.323	0.190	*
D (univ or inst info sources)	0.254	0.101	**	0.437	0.170	***
Year dummies		yes			yes	
Two-digit industry dummies		yes			yes	
Standard error				1.690	0.067	***
Correlation of the equation errors				0.286	0.102	***
Wald statistic for model			274.6 (34)			
Observations (non-zero share)			5,126 (30.0%)			

Standard errors robust to heteroskedasticity and clustered on firm. The method of estimation is maximum likelihood on a generalised Tobit model.

Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

[17] Because we also include industry and year dummies in the equation, these variables will capture only the variation within industry-year. In practice, we found that the R-squared from an equation for industry variables as a function of industry and year dummies was around 0.4, so there is considerable variability left after controlling for these variables.

We can compare these estimates to some of those for developed countries. Mairesse et al. (2005) presents an updated and extended version of the CDM model estimates for France. They also find that size, international exposure and collaboration increase the probability of doing R&D. However, they do not find that size is negatively related to R&D intensity. They also find no impact of foreign ownership on R&D, unlike in our case. For the UK, Hall and Sena (2017) also find that size, international exposure and collaboration increase the probability of doing R&D and its magnitude, and that foreign ownership is associated with higher R&D intensity. The result that foreign ownership is either zero or positive for R&D in these developed countries but negative in a developing economy like Chile's is likely to reflect the greater willingness of foreign firms to locate R&D in a more developed country.

Another interesting result from the R&D equation is that the industry variables (financial constraints, trademark use, and concentration) do not seem to influence the firm's decision to undertake R&D, while its own market share is quite important (doubling market share adds 6 percent to the probability of doing R&D and increases its level by 24 percent, other things equal). This is inline with Blundell et al. (1999) who find that market share is positively associated with the market value of innovation in UK firms and suggest that this is due to the higher incentive for pre-emptive innovation by firms with dominant positions (see also Hall and Vopel, 1997, for the U.S.).

4.3 Innovation models

There is a range of innovation indicators in the innovation survey, all measured as 0-1 variables. They include management, organizational, design, packaging, as well as the usual product and process, both new to the market and new to the firm. In addition we created two new variables for product and process innovation, one that is equal to one if the firm does any product/process innovation, and one that is equal to one if the firm does product/process innovation that is new to the firm but not to the market. The latter can be thought of as an imitator rather than an innovator. Table B-9 in the appendix shows the shares of each of these innovation variables both by observation and by firm, and Table B-10 shows their correlation. The most likely innovations are management, organizational, and any process and product, at about 40 percent of the sample. More than half the firms have either a product or process innovation. When we restrict to R&D-doers, all the shares are higher, with over 90 percent of the firms having either a product or process innovation. The correlation matrix is as expected, with all the process/product variables being correlated near 0.5, organizational and process innovation correlated, and design and product innovation correlated.

We look at two types of product innovation: the introduction of any new product during the past two years, and the introduction of a product new to the market during the past two years. The latter is closer to a true innovation, while the former will also include imitators. These innovation variables are regressed on R&D, firm size and industry, whether the firm collaborates on innovation, whether there are financial obstacles to innovation, and the sources of information about innovation. We use two versions of the R&D variable. The first is the observed log of R&D intensity (available for 30 percent of the firms) with a dummy variable for those firms that do not report R&D spending and the second is the predicted value of the log of R&D intensity from the estimates in Table 8. The latter takes into account the possibility that firms do informal R&D even if they do not report it. An alternative interpretation is that R&D intensity is being instrumented, with foreign ownership, exporting, and market share as the excluded variables.[18]

[18] Given the zeroes in actual R&D, this last interpretation is not strictly correct.

The results of estimating equation (3) are shown in Table 9 and are largely as expected: product innovation is associated with R&D, size, collaborating for innovation and using information sources. However, the presence of barriers to innovation in the form of financial constraints does not appear to matter for product innovation once we control for the R&D that might be affected by them. Surprisingly, the use of universities and basic research institutes as information sources for innovation does not seem to be associated with new to the market product innovation. The R&D results show that although doing R&D is strongly associated with product innovation, the observed intensity has a much weaker impact than the intensity predicted by the firm's size, industry, and other characteristics. This result does suggest a role for informal R&D or for R&D that is not tracked and reported to the innovation survey. Quantitatively the result is important: a doubling of R&D spending per employee implies a probability of innovation that is higher by 12 percentage points, which is large compared to the innovation probabilities of 40 and 26 percent.

Table 9

Product innovation

Dependent variable	*Product innovator*		*New-to-mkt prod innov*	
	dF/dx	*dF/dx*	*dF/dx*	*dF/dx*
R&D intensity	0.023		0.020**	
	(0.012)		(0.007)	
D (no R&D)	-0.263***		-0.145***	
	(0.061)		(0.043)	
Fitted R&D intensity		0.113***		0.126***
		(0.032)		(0.026)
Log (employment)	0.063***	0.125***	0.047***	0.107***
	(0.009)	(0.015)	(0.007)	(0.013)
D (collaborates)	0.219***	0.193***	0.155***	0.094*
	(0.042)	(0.048)	(0.039)	(0.042)
D (financial constraints)	0.009	0.029	0.013	0.029
	(0.022)	(0.021)	(0.016)	(0.016)
D (internal innov info sources)	0.240***	0.276***	0.167***	0.178***
	(0.025)	(0.026)	(0.021)	(0.023)
D (customer info sources)	0.097	0.127**	0.078*	0.116**
	(0.050)	(0.049)	(0.036)	(0.038)
D (univ or inst info sources)	0.188***	0.158***	0.049	0.011
	(0.048)	(0.048)	(0.034)	(0.034)
Year dummies	yes	yes	yes	yes
Two-digit industry dummies	yes	yes	yes	yes
Pseudo R-squared	0.318	0.259	0.278	0.228
Wald statistic for model	831.2 (31)	742.6 (30)	731.3 (31)	589.1 (30)
Share obs = 1	40.4%	40.4%	25.5%	25.5%

Marginal effects are shown; for dummy variables the impact of a change from 0 to 1 is shown.
The method of estimation is probit, with standard errors robust to heteroskedasticity and clustered on firm.

5,126 observations on 1,976 firms.

Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

4.4 Trademark use

We measure trademark use in two ways. The first defines a firm as a trademark user in all the years after its first application for a trademark, while the second measures only the presence of a trademark application during the current year. Because we expect that the use of trademarks is associated with design and packaging innovations as well as with product innovation, we include all of these in our trademark equation, along with R&D and the usual firm size and industry controls.

The results of estimation using equation (4) are in Table 10: the first 4 columns are for the trademark user variable and the last two columns for the trademark application in the current year. We find that only new-to-market product innovation is robustly associated with trademark use, although all the innovation variables enter positively. Imitative product innovation is also positively associated with the use of trademarks, but the association is only marginally statistically significant, not robust across specifications, and smaller in magnitude than the marginal effect of new-to-market product innovation.

As expected, we also find a fairly strong association between firm size and trademark use, with a doubling of size increasing the probability of using trademarks by 11 to 15 percentage points (where the average probability is 29 percent). As in the case of the innovation equation, predicted R&D intensity does a much better job of predicting trademark use than actual R&D intensity, with an increase of almost 10 percentage points in the probability of use from a doubling of R&D.

Overall, these results suggest that firms employ branding strategies to appropriate returns to their investments in (product) innovation. This finding is consistent with a long-standing survey literature that has documented the importance of this appropriation channel for innovating firms, though this literature has been confined to developed countries.[19]

[19] See WIPO (2013), Table 3.1, for an overview of relevant survey studies conducted in Japan, the Netherlands, Switzerland and the US.

Table 10

Trademark Use

Dependent variable	*D (uses trademarks)*				*D (trademark app this year)*	
	dF/dx	*dF/dx*	*dF/dx*	*dF/dx*	*dF/dx*	*dF/dx*
New-to-market product innovation	0.132***	0.112***	0.095**	0.078**	0.066**	0.049*
	(0.026)	(0.026)	(0.030)	(0.029)	(0.021)	(0.019)
Imitative product innovation	0.073**	0.060*	0.047	0.037	0.056*	0.045*
	(0.027)	(0.026)	(0.028)	(0.028)	(0.022)	(0.021)
Design innovation			0.047	0.043	0.035*	0.031
			(0.025)	(0.025)	(0.016)	(0.016)
Packaging innovation			0.027	0.020	0.026	0.020
			(0.026)	(0.026)	(0.018)	(0.018)
R&D intensity	0.009		0.009		0.008	
	(0.008)		(0.008)		(0.005)	
D (no R&D)	0.023		0.029		0.040	
	(0.041)		(0.041)		(0.027)	
Fitted R&D intensity		0.096***		0.091***		0.059***
		(0.022)		(0.022)		(0.014)
Log (employment)	0.114***	0.146***	0.112***	0.143***	0.070***	0.088***
	(0.010)	(0.013)	(0.010)	(0.013)	(0.007)	(0.009)
Year dummies	yes	yes	yes	yes	yes	yes
Two-digit industry dummies	yes	yes	yes	yes	yes	yes
Pseudo R-squared	0.162	0.169	0.164	0.171	0.144	0.149
Wald statistic for model	354.5 (29)	355.9 (28)	364.1 (31)	362.6 (30)	290.9 (31)	295.6 (30)
Share obs = 1	28.5%	28.5%	28.5%	28.5%	18.8%	18.8%

Marginal effects are shown; for dummy variables the impact of a change from 0 to 1 is shown.
The method of estimation is probit, with standard errors robust to heteroskedasticity and clustered on firm.
5,126 observations on 1,976 firms.
Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

4.5 Productivity

Table 11 shows the estimates of various specifications of equation (5). The coefficients on capital, labor, and materials are stable across specifications and similar to what other studies have found using the ENIA data (e.g. Levinsohn and Petrin, 2003). We see no statistically significant evidence that the use of trademarks is related to sales, controlling for the usual inputs. This does not change if we take into account whether a company is a product innovator. That said, the predicted probability for product innovation obtained from the product innovation regression enters positively and is statistically significant. At the mean probability of product innovation (0.4), the increase in productivity levels is 12 percent, which is considerable. For example, productivity growth in the U.S. during the past two decades is between one and three percent.[20]

Before leaving this topic, it is useful to remember that the *total factor productivity* we measure is neither *total* nor is it *productivity*, but a sort of hybrid between a profit equation and a production function. There may be omitted variables in the form of intangible capital that has been created by past investments in human capital, networks, organizational change, etc. that were expensed and are therefore not accounted for in the production

[20] https://www.bls.gov/lpc/prodybar.htm

function. The true inputs to current sales may also differ from the measured employment, capital, and materials (which may simply add to inventories, a form of tangible capital). Finally, the dependent variable incorporates both price and quantity, so that its growth captures changes in demand faced by the firm as well as any changes in the market power the firm is able to achieve. Of course, this latter problem is not a problem if we are interested in the private returns to the firm from IP use and innovative activity, as it is firm revenue that matters for that computation.

Table 11

Productivity regression

Dependent variable: Log sales (1000s pesos)

Log employees	0.320***	0.320***	0.307***	0.307***	0.307***	0.307***
(number)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Log capital	0.135***	0.135***	0.133***	0.133***	0.134***	0.134***
(1000s pesos)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log materials	0.597***	0.597***	0.591***	0.591***	0.591***	0.591***
(1000s pesos)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Trademark app this year	0.026		0.018		-0.012	
	(0.023)		(0.023)		(0.032)	
Trademark user		0.021		0.014		0.003
		(0.023)		(0.023)		(0.032)
Product innovator	0.007	0.007				
	(0.019)	(0.019)				
Predicted probability			0.306***	0.306***	0.281***	0.291***
product innovation			(0.059)	(0.059)	(0.063)	(0.070)
Trademark app &					0.089	
product innovation					(0.089)	
Trademark user &						0.036
product innovation						(0.088)
Year dummies	yes	yes	yes	yes	yes	yes
Two-digit industry dumm	yes	yes	yes	yes	yes	yes
R-squared	0.955	0.955	0.955	0.955	0.955	0.955
standard error	0.441	0.441	0.438	0.438	0.438	0.439

Standard errors robust to heteroskedasticity and clustered on firm. The method of estimation is OLS.

Trademark user has applied for trademarks any time between 1990 and the current year.

5,126 observations on 1,976 firms

Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

5. Conclusions

The empirical literature on the use of IP in developing countries has focused largely on the impact of a strengthening of patent protection on North-South technology transfer (Branstetter et al., 2006) and the link between patent protection and the availability and prices of pharmaceutical drugs (Cockburn et al., 2016; Duggan et al., 2016). Much less is known about the role of IP protection, in particular rights other than patents, in the manufacturing industry more broadly. In this context, the use of trademarks is especially interesting as the available data has shown that they are much more widely used by firms in developing countries than patents (Abud et al., 2013).

We use a new comprehensive dataset for Chile that combines detailed firm-level information from the annual manufacturing census, information on firms' innovative activities from Chile's innovation surveys, and firms' IP filings to analyze the use of IP by firms in Chile and its effect on outcomes, including growth and productivity.

Our results show that Chilean firms rely much more on the use of trademarks than patents or industrial designs. Most patents are registered by foreign firms that apparently do not have any local presence in Chile. In contrast, the majority of trademarks are registered by Chilean firms, although only a relatively small share is registered by firms in the manufacturing industry. Within manufacturing, we find that firms in chemicals (which includes pharmaceuticals) file the largest number of patents and trademarks among companies registered in Chile. Although Chile was still a middle-income economy during our sample period, the regression results that predict the use of IP and innovation mirror those of high-income countries to a great extent. We also find that the use of IP and firm growth are positively correlated. This does not imply, however, that the use of IP increases firm growth. Moreover, because the growth in inputs mirrors the growth in output for IP-using firms, it is difficult to see an impact on (revenue) TFP from IP use.

We also find that trademark use is associated with new-to-the-world product innovation, which suggests that Chilean firms employ branding strategies to appropriate returns to their investments in (product) innovation. This finding is consistent with evidence on the branding-innovation link in developed countries. In fact, taken together with the sparse use of patents across firms and over time, our results suggest that branding may be a relatively more important appropriation channel for firms in middle-income countries. Our results thus point to a sequencing of IP policies, with relatively greater emphasis placed on the trademark system at earlier development stages.

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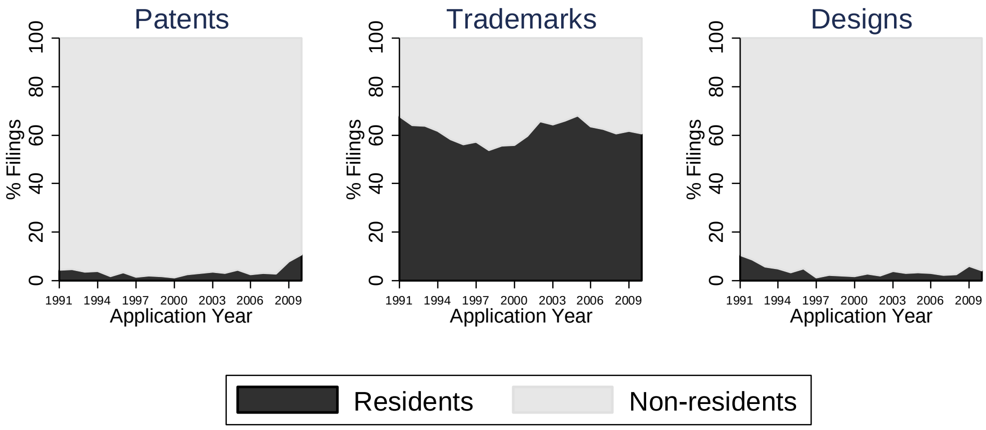
Appendix A: Additional figures

Figure A-1: Share of corporate resident vs. non-resident patent and trademark filings



Appendix B: Additional tables

Table B-1: Overview of IP use

Year	# Patenting firms	# Patent filings	Average # of patents per firm	St. dev. # of patents per firm	# TM firms	# TM filings	Average # of TMs per firm	St. dev. # of TMs per firm	# Design firms	# Design filings	Average # of Designs per firm	St. dev. # of Design per firm
1991	29	210	7.24	22.53	832	3389	4.07	7.63	20	41	2.05	2.09
1992	29	294	10.13	26.37	859	4188	4.88	11.25	18	63	3.50	5.43
1993	30	329	10.96	29.11	1000	4923	4.92	12.07	13	48	3.69	5.31
1994	40	291	7.27	13.88	924	5011	5.42	13.16	17	51	3.00	6.75
1995	29	339	11.68	19.75	937	5156	5.50	12.90	19	58	3.05	6.61
1996	40	431	10.77	19.47	932	5285	5.67	12.12	23	88	3.83	4.63
1997	37	780	21.08	55.18	972	5851	6.02	14.91	19	83	4.37	5.61
1998	46	766	16.65	43.04	932	5257	5.64	13.32	19	84	4.42	6.47
1999	38	720	18.94	37.70	867	4905	5.66	11.76	19	81	4.26	3.71
2000	44	685	15.56	34.98	889	6828	7.68	28.66	15	120	8.00	9.30
2001	35	500	14.28	28.11	875	6035	6.90	19.87	21	105	5.00	8.19
2002	44	378	8.59	17.18	861	5585	6.49	15.62	23	72	3.13	4.10
2003	47	270	5.74	12.14	897	5234	5.84	13.45	22	70	3.18	3.47
2004	47	312	6.64	15.43	917	5807	6.33	17.13	19	100	5.26	6.98
2005	59	350	5.93	16.42	971	6246	6.43	19.69	28	95	3.39	5.29
2006	48	300	6.25	16.93	936	6037	6.45	17.76	19	103	5.42	4.11
2007	51	273	5.35	12.90	928	5962	6.42	19.37	14	71	5.07	5.11
2008	50	285	5.70	13.32	879	6204	7.06	19.34	17	86	5.06	8.64
2009	51	165	3.24	4.90	698	4240	6.07	13.99	18	59	3.28	3.04
2010	38	85	2.24	2.20	709	4607	6.50	16.34	15	54	3.60	3.91
Total‡	832	7,763			17,815	106,750			378	1,532		

‡ Total number of firm-year observations.

Table B-2: Estimation sample

ENIA-IP sample

Year	# firms	# using IP (ever%)	# using patents (ever%)	# using TMs (ever%)	# using other* (ever%)	# using IP (this year)	# using patents (this year)	# using TMs (this year)	# using other* (this year)
1995	4,486	548	18	538	17	548	18	538	17
1996	5,036	853	31	835	30	550	24	531	21
1997	4,889	1,029	39	1,012	36	541	22	535	13
1998	4,636	1,144	47	1,122	44	511	26	491	17
1999	4,462	1,211	51	1,190	49	468	19	453	18
2000	4,305	1,248	53	1,227	48	425	19	417	15
2001	4,142	1,282	59	1,264	55	410	19	400	20
2002	4,590	1,420	73	1,395	64	447	22	435	19
2003	4,539	1,449	82	1,419	65	437	25	422	18
2004	4,732	1,552	98	1,515	62	462	30	439	16
2005	4,349	1,608	105	1,571	73	488	30	467	24
Total	**50,166**	**13,344**	**656**	**13,088**	**543**				

*other is utility models or design patents.

% ever means the firm this year or earlier used the IP protection method.

Table B-3: Industry distribution

Sectoral distribution of ENIA-IP sample

ISIC2	*Industry*	*# obs*	*# firms*	*Share*	*Emp wtd**	*Share*
15, 16	food products and beverages, tobacco	14,701	2,275	29.1%	208,120	34.3%
17	textiles	2,934	433	5.5%	21,981	3.6%
18	wearing apparel; dressing and dyeing of fur	3,254	554	7.1%	30,000	4.9%
19	leather preparation & goods	1,791	275	3.5%	17,686	2.9%
20	wood, cork and straw products, ex furniture	3,448	571	7.3%	60,829	10.0%
21	paper and paper products	1,299	193	2.5%	18,125	3.0%
22	publishing, printing and reproduction of recorded media	2,249	368	4.7%	19,251	3.2%
23, 24	chemicals and chemical products incl coke & refined oil	2,657	376	4.8%	44,681	7.4%
25	rubber and plastics products	3,201	466	6.0%	29,292	4.8%
26	other non-metallic mineral products	1,750	262	3.4%	20,690	3.4%
27	basic metals	951	137	1.8%	36,205	6.0%
28	fabricated metal products, except machinery & equipment	4,092	662	8.5%	38,190	6.3%
29	machinery and equipment n.e.c.	2,678	421	5.4%	19,135	3.2%
30, 31, 32	electrical machinery and apparatus, comp. machinery	989	150	1.9%	6,673	1.1%
33	medical, precision & optical instruments, watches & clocks	326	40	0.5%	2,020	0.3%
34	motor vehicles, trailers and semi-trailers	813	119	1.5%	5,242	0.9%
35	other transport equipment	411	61	0.8%	6,902	1.1%
36	furniture; manufacturing n.e.c.	2,622	443	5.7%	22,137	3.6%
	Total	**50,166**	**7,806**		**607,159**	

* weighted by employment in the last year.

IP use by Sector

		*Ever**					*Shares that ever*				
ISIC2	*# firms*	*used any IP*	*used patents*	*used TMs*	*used design rights*	*used utility models*	*used any IP*	*used patents*	*used TMs*	*used design rights*	*used utility models*
15, 16	2,275	1,111	23	1,103	25	8	48.8%	1.0%	48.5%	1.1%	0.4%
17	433	239	3	237	1	2	55.2%	0.7%	54.7%	0.2%	0.5%
18	554	316	1	315	0	0	57.0%	0.2%	56.9%	0.0%	0.0%
19	275	166	4	164	6	1	60.4%	1.5%	59.6%	2.2%	0.4%
20	571	252	10	251	1	4	44.1%	1.8%	44.0%	0.2%	0.7%
21	193	106	6	106	4	5	54.9%	3.1%	54.9%	2.1%	2.6%
22	368	183	6	180	1	1	49.7%	1.6%	48.9%	0.3%	0.3%
23, 24	376	266	40	266	23	5	70.7%	10.6%	70.7%	6.1%	1.3%
25	466	279	33	271	23	11	59.9%	7.1%	58.2%	4.9%	2.4%
26	262	151	9	151	2	1	57.6%	3.4%	57.6%	0.8%	0.4%
27	137	82	17	80	2	3	59.9%	12.4%	58.4%	1.5%	2.2%
28	662	315	11	311	6	4	47.6%	1.7%	47.0%	0.9%	0.6%
29	421	203	9	198	3	2	48.2%	2.1%	47.0%	0.7%	0.5%
30, 31, 32	150	80	1	79	4	1	53.3%	0.7%	52.7%	2.7%	0.7%
33	40	28	2	28	0	0	70.0%	5.0%	70.0%	0.0%	0.0%
34	119	63	5	62	1	1	52.9%	4.2%	52.1%	0.8%	0.8%
35	61	33	1	33	0	0	54.1%	1.6%	54.1%	0.0%	0.0%
36	443	221	4	217	4	2	49.9%	0.9%	49.0%	0.9%	0.5%
	7,806	**4,094**	**185**	**4,052**	**106**	**51**	**52.4%**	**2.4%**	**51.9%**	**1.4%**	**0.7%**

* Number that applied for the IP type at least once during the period 1990-2005.

Table B-4: Hirschman-Herfindahl Index and Sales by Foreign Firms

4-digit industry characteristics by 2-digit industry

Industry	*All*	*Mean HHI*	*HHI>2500*	*Share*	*Share foreign-owned sales*
food products and beverages, tobacco	169	2554	61	36.1%	10.6%
textiles	74	1324	15	20.3%	4.9%
wearing apparel; dressing and dyeing of fur	11	663	0	0.0%	3.9%
leather preparation & goods	34	1268	2	5.9%	1.1%
wood, cork and straw products, ex furniture	58	1785	11	19.0%	6.6%
paper and paper products	33	1813	10	30.3%	13.3%
publishing, printing and reproduction of recorded media	67	3283	38	56.7%	24.7%
chemicals and chemical products incl coke & refined oil	105	3025	49	46.7%	26.9%
rubber and plastics products	35	2808	23	65.7%	39.2%
other non-metallic mineral products	87	3048	51	58.6%	6.5%
basic metals	22	2552	13	59.1%	12.0%
fabricated metal products, except machinery & equipment	87	2456	30	34.5%	4.1%
machinery and equipment n.e.c.	143	2575	48	33.6%	2.3%
electrical machinery and apparatus, comp. machinery	95	3544	51	53.7%	9.3%
medical, precision & optical instruments, watches & clocks	46	4117	36	78.3%	33.9%
motor vehicles, trailers and semi-trailers	34	4208	13	38.2%	16.2%
other transport equipment	50	5151	41	82.0%	1.9%
furniture; manufacturing n.e.c.	64	2902	31	48.4%	1.8%
Total	**1,214**	**2789**	**523**	**43.1%**	**11.2%**

Table B-5: Variable means

Simple statistics for the estimation sample

	*mean**	*sd*	median	*p25*	*p75*	*min*	*max*
Sales per employee (1000s of pesos)	16410.4	0.913	14528.9	9060.53	26904.3	312.4	3,043,534
Number of employees	37.34	1.073	29	17	67	2	9,187
Capital per employee (1000s of pesos)	3590.5	1.608	4036.2	1467.7	10014.7	0.0	2,621,848
Materials per employee (1000s of pesos)	5618.8	1.147	5185.8	2873.1	10891.9	7.5	1,569,253
Firm market share	0.0030	1.941	0.0023	0.0007	0.0113	0	1
4-digit industry Herfindahl	824.8	0.921	770.1	415.7	1659.7	135.9	10,000
N of design patent apps	0.014	0.425	0	0	0	0	37
N of patent apps	0.061	2.119	0	0	0	0	176
N of trademark apps	0.542	4.065	0	0	0	0	210
N of utility model apps	0.001	0.042	0	0	0	0	5
	Dummy variables						
D (foreign ownership)	2.7%						
D (foreign & domestic ownership)	2.4%						
D (public ownership)	0.6%						
D (sole proprietorship)	16.8%						
D (exporter)	20.5%						
D (Santiago metro region)	59.2%						
D (ever applied for patent 1995-2005)	1.3%						
D (ever applied for trademark 1995-2005)	26.1%						
D (ever applied for design patent 1995-2005)	0.8%						
D (IP app in current year)	10.5%						
D (first time IP user 1996-2005)	9.3%						
D (prior IP user on entry)	36.5%						

* Geometric mean for the first 5 variables.

50,166 observations

Table B-6

Comparing TFP Estimation methods

Dep var = Log(revenue)

	OLS	*Olley-Pakes*	*Levinsohn-Petrin*	*ACF (materials)*
Log (capital stock)	0.091	0.050	0.056	0.075
	(0.004)	(0.005)	(0.021)	(0.004)
Log (employment)	0.415	0.369	0.355	0.320
	(0.010)	(0.006)	(0.010)	(0.037)
Log (materials)	0.589	0.562	0.363	0.682
	(0.006)	(0.005)	(0.157)	(0.022)
Scale coefficient	1.095***	0.981*	0.774	1.077***
	(0.012)	(0.009)	(0.159)	(0.043)
P-value for CRS	0.000		0.949	0.001
Instruments	--	--	Capital, lagged capital, employment, & materials	Capital, lagged capital, employment, & materials

All equations include year dummies.

Standard errors are bootstrap with 20 draws.

Chilean manufacturing data, 40,841 observations on 7,740 firms, 1996-2005.

Table B-7

ACF estimates of the production function

Industry	*15 food & beverage*	*17 textiles*	*18 wearing apparel*	*19 leather*	*20 wood, cork, straw*	*21 paper*	*22 publishing & printing*	*24 chemicals*	*25 rubber & plastics*
Observations	12,067	2,356	2,592	1457	2,737	1066	1,816	2191	2,655
Firms	2,263	427	549	270	562	189	364	375	465
Log (capital stock)	0.062	0.085	0.054	0.068	0.081	0.090	0.028	0.132	0.075
	(0.020)	(0.034)	(0.036)	(0.009)	(0.026)	(0.035)	(0.011)	(0.320)	(0.008)
Log (employment)	0.264	0.310	0.934	0.563	0.346	0.332	0.456	0.325	0.365
	(0.105)	(0.340)	(0.298)	(0.041)	(0.224)	(0.964)	(0.054)	(0.145)	(0.022)
Log (materials)	0.720	0.645	0.265	0.549	0.639	0.661	0.641	0.638	0.627
	(0.113)	(0.278)	(0.350)	(0.041)	(0.125)	(0.540)	(0.034)	(0.150)	(0.014)
Scale coefficient	1.046	1.040	1.253	1.180	1.066	1.083	1.125	1.095	1.067
	(0.156)	(0.440)	(0.461)	(0.059)	(0.258)	(1.105)	(0.065)	(0.382)	(0.027)
P-value for CRS	0.666	0.374	0.012	0.000	0.345	0.141	0.000	0.000	0.000

	26 other non-metal prods	*27 basic metals*	*28 fabricated metal*	*29 machinery & eq*	*31 elec & computing machinery*	*33 instruments*	*34 motor vehicles*	*35 other transport eq*	*36 furniture & mfg NEC*
Observations	1434	788	3,296	2,166	822	267	670	334	2,106
Firms	260	137	655	416	150	40	119	60	439
Log (capital stock)	0.067	0.096	0.081	0.088	0.075	0.102	-0.053	0.153	0.096
	0.020	(0.026)	(0.010)	(0.030)	(0.014)	(0.040)	(0.023)	(0.036)	(0.007)
Log (employment)	0.466	0.382	0.417	0.449	0.416	0.380	0.311	-0.005	0.412
	(0.058)	(0.051)	(0.038)	(0.201)	(0.255)	(0.135)	(0.163)	(0.159)	(0.027)
Log (materials)	0.662	0.621	0.592	0.515	0.652	0.527	0.702	0.812	0.578
	(0.028)	(0.022)	(0.036)	(0.181)	(0.092)	(0.058)	(0.105)	(0.133)	(0.018)
Scale coefficient	1.195	1.099	1.090	1.052	1.143	1.009	0.960	0.960	1.086
	(0.067)	(0.061)	(0.053)	(0.272)	(0.271)	(0.152)	(0.195)	(0.210)	(0.033)
P-value for CRS	0.062	0.000	0.000	0.000	0.046	0.053	0.645	0.866	0.000

Table B-8: Innovation sample R&D performance

Sectoral distribution of the Innovacion-ENIA-IP sample

			Number		*Share*	
Industry	*# obs*	*# firms*	*Continuous R&D*	*Occasional R&D*	*Continuous R&D*	*Occasional R&D*
food products and beverages, tobacco	1050	400	79	62	19.8%	15.5%
textiles	252	97	12	13	12.4%	13.4%
wearing apparel; dressing and dyeing of fur	213	96	9	8	9.4%	8.3%
leather preparation & goods	184	73	8	13	11.0%	17.8%
wood, cork and straw products, ex furniture	355	150	13	18	8.7%	12.0%
paper and paper products	233	81	13	16	16.0%	19.8%
publishing, printing and reproduction of recorded media	223	98	6	9	6.1%	9.2%
chemicals and chemical products incl coke & refined oil	463	154	49	41	31.8%	26.6%
rubber and plastics products	355	131	20	23	15.3%	17.6%
other non-metallic mineral products	251	91	17	21	18.7%	23.1%
basic metals	266	83	18	21	21.7%	25.3%
fabricated metal products, except machinery & equipment	334	145	22	18	15.2%	12.4%
machinery and equipment n.e.c.	266	114	14	18	12.3%	15.8%
electrical machinery and apparatus, comp. machinery	174	64	11	10	17.2%	15.6%
medical, precision & optical instruments, watches & clocks	80	25	4	4	16.0%	16.0%
motor vehicles, trailers and semi-trailers	113	44	4	6	9.1%	13.6%
other transport equipment	85	30	3	7	10.0%	23.3%
furniture; manufacturing n.e.c.	229	100	8	14	8.0%	14.0%
Total	**5,126**	**1,976**	**310**	**322**	**15.7%**	**16.3%**

Table B-9

Innovative activity

	All firms		*R&D-doers only*	
Type of innovation	*Share of observations*	*Share of firms*	*Share of observations*	*Share of firms*
Management innovation	40.6%	44.0%	68.7%	79.1%
Organizational innovation	38.7%	42.5%	66.5%	77.4%
Design innovation	30.9%	34.4%	57.3%	65.2%
Packaging innovation	19.1%	22.0%	38.2%	46.0%
Any process innovation	42.7%	44.7%	76.0%	82.8%
Process new to market	22.8%	25.8%	48.4%	57.9%
Process new to firm	38.8%	41.9%	67.6%	77.1%
Process new to firm, not to mkt	20.0%	26.4%	27.5%	44.5%
Any product innovation	40.4%	42.7%	76.1%	82.6%
Product new to market	25.5%	27.0%	54.4%	59.5%
Product new to firm	35.2%	39.0%	65.8%	75.8%
Product new to firm, not to mkt	14.9%	20.5%	21.7%	34.8%
Any product or process innovation	51.9%	53.0%	89.3%	93.2%
Observations	5,126	1,976	1,536	632

Table B-10: Raw correlations of the innovation variables

	mgmt	*org*	*design*	*package*	*proc*	*proc - mkt*	*proc-firm*	*proc imitator*	*prod*	*prod-mkt*	*prod-firm*	*prod imitator*	*prodproc*
mgmt	1												
org	0.7251	1											
design	0.4556	0.4745	1										
package	0.3862	0.4082	0.4672	1									
proc	0.5061	0.5486	0.4986	0.3812	1								
proc - mkt	0.3916	0.4484	0.3941	0.3591	0.6292	1							
proc-firm	0.4676	0.4996	0.4489	0.3547	0.9224	0.4914	1						
proc imitator	0.2158	0.2087	0.2039	0.0952	0.5781	-0.2705	0.6267	1					
prod	0.4823	0.5132	0.5878	0.4331	0.5778	0.4587	0.5203	0.234	1				
prod-mkt	0.3824	0.4304	0.5086	0.3895	0.4420	0.4892	0.3753	0.0339	0.7113	1			
prod-firm	0.4498	0.4817	0.5324	0.4121	0.5470	0.4276	0.5237	0.2286	0.8948	0.5441	1		
prod imitator	0.1966	0.1803	0.1874	0.1201	0.2553	0.0332	0.2577	0.2813	0.5077	-0.2445	0.5674	1	
prodproc	0.5610	0.5789	0.5602	0.4055	0.8321	0.5236	0.7676	0.4810	0.7940	0.5647	0.7104	0.4031	1

Shaded correlations are those greater than 0.5.

Appendix C: Variable description

Source is ENIA

- Log sales - log of total revenue, in 1000 pesos.
- Log employment – log of the sum of the total average employees with and without a contract.
- D (foreign owner) – Dummy=1 if the form of ownership is 2 (privada extranjera).
- D (exporter) – Dummy=1 if the revenue from exports is greater than zero.
- Log firm market share in 4-digit sector – constructed from total revenue and all the firms in the ENIA survey, using ISIC version 3.
- Log HHI in 4-digit sector – constructed from total revenue and all the firms in the ENIA survey, using ISIC version 3.
- Log capital stock – log of the nominal value of fixed capital stock, in 1000 pesos.
- Log materials – log of total raw and purchased materials, in 1000 pesos.
- Industry dummies based on 2-digit ISIC version 3, with slight recoding shown in Table B-3.

Source is *Innovacion*

- R&D spending – for 1997, 1998, 2000, 2001, total R&D spending (I+D). For 2003-2005, the sum of basic, applied, and experimental R&D using own funds and funds from government, international, and others.
- D (collaborates) – Dummy=1 if firm cooperated with other firms or institutions in innovation. Only available for 2003-2005 surveys, others set to zero (year dummies are therefore essential).
- Industry financial constraints – mean barriers to innovation within industry-year, where a financial barrier is defined as inadequate funding>2 or payback period too long>2 (both on a 0-4 point Likert scale).
- Industry trademark use – mean of trademarks/sales within industry-year, in trademarks per billion pesos.
- D (internal innov info sources) - Dummy=1 if importance of internal R&D or group R&D for innovation ideas>2 (on at 0-4 point Likert scale)
- D (customer info sources) - Dummy=1 if importance of customer/client ideas for innovation ideas>2 (on at 0-4 point Likert scale). Not available for surveys 2003-2005, set to zero (year dummies are therefore essential).
- D (university or institution info sources) - Dummy=1 if importance of university or PROs for innovation ideas>2 (on at 0-4 point Likert scale)