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# INTELLECTUAL PROPERTY USE IN MIDDLE INCOME COUNTRIES: THE CASE OF CHILE

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**ABSTRACT**

A frequently debated question is whether the use of intellectual property (IP) protection benefits the residents of low and middle income countries. We contribute to this debate with an analysis of the use of patents and trademarks by firms in Chile over the decade 1995-2005 as the then middle-income country experienced rapid economic growth. Using a novel dataset containing the merge of detailed firm-level information from the annual manufacturing census with firms' patent and trademark filings with the Chilean IP office, we look at how IP use by companies has changed over time and analyze the determinants of and outcomes from their use, in particular first-time use. We find that firm 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.

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## 1. Introduction

There is a long-standing and contentious debate on the impact of intellectual property (IP) rights, mostly in the form of patents, on economic development (Penrose, 1973; Primo Braga, 1990a). Early theoretical analysis suggested that developing countries would be worse off if they adopted IP systems similar to those in existence in developed economies (Deardorff, 1992; Helpman, 1993). However, this literature focused on a stylized setting, in which developing countries imitate innovation created by developed economies. The theoretical predictions are more ambiguous if developing countries can become innovators instead of relying exclusively on imitation (Chen and Puttitanun, 2005). In such a setting, it is still possible that developing countries benefit from weak IP protection as it allows domestic firms to absorb and build on foreign technology at lower cost (Branstetter, 2017). On the other hand, stronger IP protection could promote local innovation and thereby economic development through several mechanisms (Primo Braga, 1990a). IP can stimulate technology transfer from developed to developing economies, for example through licensing (Branstetter et al., 2006) and foreign direct investment (FDI) (Javorcik, 2004). It could also provide increased incentives for developing country firms to invest in R&D (Maskus, 2000).

By now, there is considerable empirical evidence on the impact of patenting on companies in the industrialized world, above all the U.S., Japan, and Europe. The evidence to date suggests that in developed economies, ownership of patents is associated with higher employment and sales growth, higher productivity, and higher firm value (e.g., Hall et al., 2005; Balasubramanian and Sivadasan, 2011; Hall et al., 2013; Farre-Mensa et al., 2019). There are also empirical studies on the impact of patent systems in developing countries, focusing in particular on the impact caused by a strengthening of IP systems as a consequence of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS); for a survey of the literature see Hall (2014). In general, the results suggest that stronger patent protection encourages FDI and technology transfer to developing economies. However, there is mixed evidence on the impact of stronger patent protection on indigenous innovation in developing countries (Branstetter, 2004; Schneider, 2005). In particular, 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). This reflects the so-called "stages approach" to IP, which assumes that the trade-off between allowing imitation of existing innovation and encouraging innovation by granting effective IP protection depends on the stage of development of an economy (Primo Braga, 1990b). This implies that a distinction between low- and middle-income developing countries is useful in the analysis of the impact of IP on economic development.

With the exception of China, the available empirical evidence on the impact of IP on domestic innovation and economic development relies largely on aggregate, cross-country comparisons (e.g. Gold and Gruben, 1996; Kanwar and Evenson, 2003; Hu and Png, 2013). This is problematic, for several reasons. First, cross-country econometric analyses typically rely on aggregate proxy measures of the strength of patent protection. These are bound to only imperfectly capture the incentives faced by innovating firms (Fink and Raffo, 2019).[4] Second, such analyses often implicitly assume that patents flow seamlessly from rich to poor countries. This is, in fact, not the case, as patenting is a costly undertaking. Evidence suggests that, aside from China, less than 5 per cent of inventions patented in high-income economies are also patented in low- and middle-income economies (Fink and Raffo, 2019). Third, the strength of IP protection is not an exogenous variable when trying to explain aggregate growth outcomes and econometric techniques can only imperfectly control for the resulting endogeneity. Finally, cross-country analysis necessarily assumes that a universal relationship exists between patent protection and development outcomes that transcends the varying structural features and policy environments across developing economies. Such an expectation may not necessarily hold; or at least, it may not be possible to econometrically control for the varying local contexts in which a patent system operates.

Studying the impact of IP protection at the firm-level in specific economies can enable deeper insights into how patent rights affect economic performance in developing economies. Few such firm-level studies are available. Exceptions are Deolalikar and Röller (1989) focusing on Indian firms, and Kim et al. (2009 and 2014) focusing on Korean industries and firms. These studies find a positive association between total factor productivity (TFP) and patenting performance. However, they view patenting as an (intermediate) knowledge output. They do not analyze how patent use directly affects TFP.

Another limitation of the existing literature is that it focuses almost exclusively on patents. In practice, other forms of IP, notably trademarks, are much more frequently used, especially in countries at lower levels of economic development (WIPO, 2013). Trademarks could have a substantial effect on firm performance in developing countries as recent empirical evidence for the U.S. suggests that first-time trademarking is associated with higher employment and revenue growth (Dinlersoz et al., 2018).

Broadening the focus to include both patents and trademarks is important because these two IP rights cover different aspects of a company's intangible assets. Patents cover inventions that are considered solutions to a technical problem. Patents are granted to eligible inventions that are novel and non-obvious, which means that they do not yet exist anywhere in the world. Trademarks in contrast have no novelty requirement. They are granted on any words and symbols that represent product and company brands. Trademarks merely require that there is no existing, confusingly similar mark on the national trademark register. This reflects the trademark system's main objective to lower consumer search costs by granting exclusive rights to the use of a distinguishable sign. As a result, trademarks are relevant for a much larger set of companies including those that do not engage in novel innovative activity. Still, the empirical evidence suggests that trademarking is strongly associated with innovative activity (Schautschick and Greenhalgh,

[4] The most frequently used proxy measure is index of patent strength developed by Park (2008). While covering a wide set of countries over several decades, it focuses only on selected elements of patent law and membership in international treaties, with arbitrary weights attached to them. In addition, it only imperfectly captures how patents are prosecuted and enforced in practice.

2016). Therefore, both types of IP encourage investment in intangible assets and improve company performance.

In this paper, we explore the effect of the use of IP in the form of both patents and trademarks on manufacturing firms in Chile between 1995 and 2005. We are 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? Our analysis of first-time IP use is also motivated by a major reform of the Chilean IP system in 1991. The reform strengthened IP protection in Chile and therefore likely increased incentives for firms to use patents and trademarks.

This analysis is possible thanks to a novel, rich data source from Chile that includes production and IP ownership 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). The matched manufacturing census data cover the period 1995-2005. The IP data for all firms are available over the entire 1991-2010 period. The panel structure and the two decades long time series of IP use allow us to analyze changes in the use of IP by companies and to relate IP use to company characteristics and performance. Apart from its broad coverage, the data also stand 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. The country saw stable macroeconomic conditions and rapid GDP per capita growth of almost 4 per cent a year, which eventually led the country to transition from middle- to high-income status in 2012. Manufacturing output doubled in real terms from 1991 to 2010 and manufacturing value added grew at an average annual rate of 3.5 percent.[5] It is in this context that our analysis investigates whether IP has contributed in any significant way to improved performance at the firm-level in form of growth or productivity.

Our results therefore enrich the existing evidence on IP use and firm performance in Chile and more generally in middle-income developing 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.

We find that foreign-owned firms hold more patents than suggested by their numbers (only 3 per cent of all firms), but far fewer trademarks. Domestic firms, in contrast, file very few patents, but instead engage frequently with the trademark system. 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

[5] Based on figures from the World Bank's World Development Indicators database.

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, once we control for the overall level of use.

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). That said, when we look at trademarking and patenting more broadly beyond just first-time use, we find that trademarking is associated with higher productivity, while patenting is not. These findings differ from some of the results for high-income countries (Balasubramanian and Sivadasan, 2011; Greenhalgh and Rogers, 2012; Dinlersoz et al., 2018). In the case of patents, 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 decade used in our regression analysis. In the case of trademarks, the evidence is more mixed. First-time trademarking does not appear to alter the growth trajectory of firms, but we do find a positive association between trademarking beyond first-time filing and productivity.

Overall, our results allow us to draw several conclusions about the potential role of IP in the development process of middle-income economies. First, the existence of a patent system is not sufficient to jumpstart innovation in a middle income country, as evidenced by the few domestic firms that make use of it. Second, we find little evidence that entering the IP system increases revenue productivity (which is essentially the profitability) of domestic firms. Third, companies that start using the IP systems are already growing, that is, growth leads to IP use. Finally, our results also suggest that in middle income countries, trademarks are likely to be a more important form of IP protection than patents. Trademarks support the branding of new products and may thus help firms in appropriating returns to new products and services, but do not require that these products be on the global technology frontier.

The remainder of this paper is organized as follows. Section 2 briefly discusses the existing literature on why firms choose to patent and/or trademark and the impact that choice has on performance. Section 3 provides a short overview of the Chilean patent and trademark systems. Section 4 describes the data used in our analysis. Section 5 provides our empirical results, looking at IP use by firms and its impact on their performance. Section 6 offers a few concluding remarks.

# 2. The Use of Patents and Trademarks

## 2.1 Patents

Firms' use of different IP instruments is motivated by their business activities and competitive strategies. One strategy to gain an edge over rivals is to innovate and introduce new products to the market. To the extent that innovation pushes the technology frontier, firms may seek patent protection for their inventions to make imitation by rivals more difficult. Patenting therefore enables firms to potentially decrease competition and earn profits from innovating that exceed those they would earn in the absence of patent protection. Patents can also facilitate technology licensing and therefore offer another source of revenue for innovators. That said, patenting is costly and requires the disclosure of the invention, and enforcement through court action is expensive and potentially a lengthy and complex procedure, which may lead firms to forgo patenting even when they have patentable inventions (for detailed discussion, see Hall et al., 2014).

This might help explain the stylized fact that emerges from the existing literature that patenting is rare even in high-income economies: 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, patent registration data for a number of countries – with the exception of China – suggest that domestic companies hold only a very small number of patents (Abud et al., 2013; Kaboré, 2011).

The available empirical evidence on developed economies suggests that firms benefit substantially from patenting. Balasubramanian and Sivadasan (2011) for example report 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. There is also a substantial body of evidence that suggests a positive association between patenting and productivity growth (Lach, 1995; Crepon et al., 1998; Bloom and van Reenen, 2002). Productivity is usually computed using revenue as the output variable which means that any effect of patents on productivity is driven by both the impact of lower production costs due to process innovation and a firm's ability to raise price and hence mark-up due to product innovation.

### 2.2 Trademarks

The absence of a global novelty requirement for trademarks implies that there are less 'entry barriers' to their use – especially in a country that is not generally on the technology frontier. In other words, Chilean firms will generally find it easier to obtain a trademark for a product innovation than a patent on the underlying technology.

Trademarks help appropriate investments in innovation in a variety of ways. As consumers are asymmetrically informed about (newly introduced) products, firms rely on the reputation mechanism created by brand recognition which is protected by trademarks to induce consumer purchases (Akerlof, 1970; Landes and Posner, 1987). In addition, one would expect more successful innovators to take out more trademarks. As originally argued by Nelson (1970), sellers of high-quality products have a greater incentive to engage in product branding to persuade consumers to try their goods, because the present value of a trial purchase is larger than in the case of low-quality producers.

Evidence from high-income countries confirms that trademarks, R&D investments, and patents are complements (Dinlersoz et al., 2018). Similarly, evidence from European innovation surveys shows that innovative manufacturing firms are more likely to use trademarks than non-innovative ones (WIPO, 2013).

However, branding not only serves reputational purposes; it can create and sustain so-called image value. A consumer facing the choice between two goods of the same quality, but bearing different brand names, may still choose one brand over another – and may even be willing to pay a higher price for the preferred brand. This means that brands can produce product differentiation in the perception of consumers (Lancaster, 1984), and therefore confer companies some degree of market power. The marketing literature offers in fact plenty of evidence that well-known brands often dominate markets for extensive periods of time (for a review see Bronnenberg and Dube, 2017). Resulting increases in mark-ups could translate into improved firm performance in the form of productivity (Greenhalgh and Rogers, 2012).

While brand image is often associated with innovative products, it does not have to be so. Sutton (1991) and Ofek and Savary (2003) consider a firm's choice to product differentiate either through technological innovation or through persuasive advertising. Their findings suggest that incentives for product differentiation based on persuasive advertising are higher if firms' R&D capabilities are weaker and if markets are more mature and there are fewer opportunities for introducing truly new products. These considerations suggest that firms in middle-income countries may rely more strongly on branding in their product differentiation strategies, and the complementary relationship between patents and trademarks may well be weaker.

# 3. The IP system in Chile

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 and therefore represents a major change in Chile's IP system. Among others, the 1991 law introduced product and process patents on food, pharmaceuticals and chemicals.[6] This means that since 1991, active chemical and pharmaceutical ingredients could be patented whereas before 1991 only the production process was patentable. Since then the law has undergone three amendments. However, they all took effect after the end of our sample period so we ignore them here (they are discussed in Abud et al., 2013).

## 3.1 Patents

Chile's 1991 Law on Industrial Property implemented most provisions later included in TRIPS. Note that Chile entered the Patent Cooperation Treaty (PCT) only in 2009, which means that during our sample period, in order to obtain patent protection in Chile, patents had to be filed directly with the

[6] The 1991 law also allowed for so-called "revalida" patents. Regardless of a patent's priority date, patents granted or pending in other jurisdictions could be filed in Chile, and granted in Chile for the remaining statutory validity period in the country of origin or 15 years from the date of grant whichever was shorter. Revalida patents were eliminated from the system by a 2005 amendment. For more details see Appendix 1 in Abud et al. (2013).

national patent office.[7] There are few characteristics of the Chilean patent system worth highlighting. For example, in Chile, software *per se* is not patent eligible and protected by copyright. Also, before the 2005 amendment,[8] the statutory lifetime of a patent was 15 years from the grant date. The amendment changed this into 20 years from the date of filling. Moreover, during our period of analysis, invalidation of a granted patent was only possible within 10 years counting from the date of grant.[9] Finally, to obtain a patent in Chile, applicants incur different fees, which add up to approximately US$ 1,100.

### 3.2 Trademarks

Trademarks are defined as signs that distinguish products, services, or industrial and commercial establishments in the market. A trademark can be a word, symbol or combination of both. Chile is not part of the Madrid System for the International Registration of Marks, which means that non-resident applicants have to file directly with INAPI to obtain a trademark in Chile. Trademark rights are examined in Chile on absolute and relative grounds. They last for a period of 10 years from the grant date but can be renewed indefinitely. Unlike some other countries, INAPI does not require the applicant to prove actual use of the trademark, neither at the initial filing stage nor at the renewal stage. Also note that until 2012, applicants had to file separate applications if they wanted trademark protection in product as well as service classes. The fees to register a trademark are considerably lower than for patents adding up to only around US$ 300, although the cost can be larger depending on the number of classes covered by the trademark.

## 4. Data

The data consists of two components: (1) INE's manufacturing census *ENIA*, and (2) INAPI's IP data, which includes trademarks, patents, design rights, and utility models.[10] In this section we briefly describe these two 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.

### 4.1 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. 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).

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[7] The PCT offers a patent filing system to obtain patent protection in all contracting states worldwide through a single application.

[8] The 2005 amendment took effect in December 2005 and is therefore not covered by our data.

[9] The 2005 amendment reduced this to 5 years.

[10] Chile only introduced a system for protecting non-agricultural geographical indications in 2005, just at the end of our sample period. For this reason, we exclude this form of IP right from our analysis.

## 4.2 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.[11,12] 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.[13] 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 the major reform of the IP system came into effect (see Section 3 above).

In this paper we use only the patent and trademark data from the INAPI database. Few Chilean firms in our sample make use of design rights or utility models (about one per cent for each). For further information on the use of these forms of IP in Chile, see Abud et al. (2013).

## 4.3 Combining ENIA and IP data

With the help of the INE, we combined the ENIA 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.[14] 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 data cover the period 1995-2005. Note that the ENIA 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 fairly long time series to analyze changes in the use of IP by companies and to relate IP use to company characteristics and performance.

## 4.4 Data description

Table 1 provides an overview of the available data. The table shows that we have on average nearly 5,000 firms per year in the ENIA between 1995 and 2005, a total of 9,279 unique firms.

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[11] 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.

[12] In what follows, we discard the data on industrial designs and utility models as there are few of these. See Fink et al. (2018) for analysis that includes industrial designs.

[13] 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 includes IP filings by foreign-owned companies registered in Chile.

[14] 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: Overview of data coverage**

| | *All* | *Patent* | | *Trade-mark* | |
|---|---|---|---|---|---|
| *Year* | *Number of firms* | *Number of firms* | *%* | *Number of firms* | *%* |
| 1995 | 4,957 | 19 | 0.38% | 572 | 11.54% |
| 1996 | 5,275 | 27 | 0.51% | 556 | 10.54% |
| 1997 | 5,044 | 22 | 0.44% | 551 | 10.92% |
| 1998 | 4,785 | 29 | 0.61% | 508 | 10.62% |
| 1999 | 4,671 | 21 | 0.45% | 471 | 10.08% |
| 2000 | 4,544 | 21 | 0.46% | 444 | 9.77% |
| 2001 | 4,464 | 20 | 0.45% | 434 | 9.72% |
| 2002 | 4,785 | 24 | 0.50% | 452 | 9.45% |
| 2003 | 4,766 | 27 | 0.57% | 438 | 9.19% |
| 2004 | 4,993 | 31 | 0.62% | 461 | 9.23% |
| 2005 | 5,034 | 33 | 0.66% | 507 | 10.07% |
| Total# | 53,318 | 274 | 0.51% | 5,394 | 10.12% |
| Unique* | 9,279 | 141 | 1.52% | 2,502 | 26.96% |

# Total number of firm-year observations.

* Unique number of firms.

Table 1 also shows the results from the match with the IP data.[15] Additional detail on the match is shown in Appendix Table B-1. The match rates seem relatively low. In the case of patents, this is doubtless because most patents are taken out by foreign firms that are not in our sample (i.e., do not have a Chilean manufacturing plant). In the case of trademarks, many are held by individuals or non-manufacturing firms and will therefore not match to ENIA. Because we do not have access to the ENIA data containing the firm names, we are not able to report on the presence of false negatives, that is, firms that should have matched and did not. But given the RUT-level matching, there is no reason to think that the number of these is large.

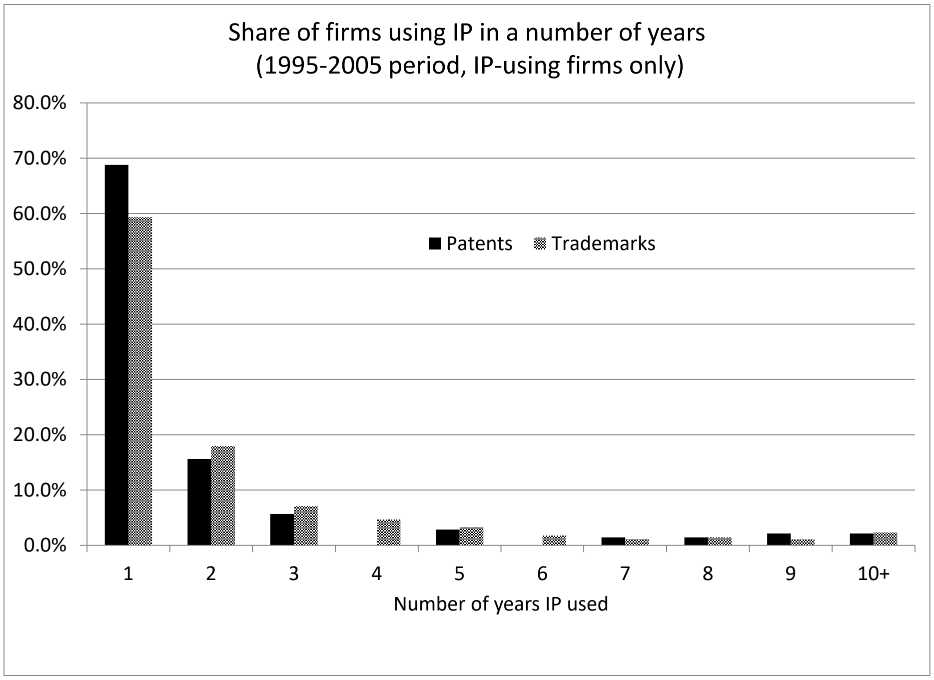
The data show that relatively few ENIA firms patent; 141 firms covered by the ENIA have filed for at least one patent between 1995 and 2005. The number of trademarking firms is much larger: 27% of firms covered by the ENIA filed for at least one trademark between 1995 and 2005. These findings are in 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 and trademark filings by Chilean applicants among all patent and trademark filings by companies over the entire 1991-2010 period (that is, including foreign companies). The figure shows the small share of patents 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 11-year period of our sample, 1995-2005. The distributions are similar in that more

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

than half of firms that patent or trademark do so in a single year during the 11-year period, very few companies do so in several years and hardly any company every year. The distribution for trademarks is slightly to the right of that for patents, but not by very much.

**Figure 1: Number of years in which firms patent/trademark (1995-2005)**




## 5. IP use and performance

Next we describe the use of patents and trademarks by Chilean manufacturing companies over the period 1995-2005 and explore the determinants of their use, in particular first-time use. We then go on to analyze the short and medium-term effects of using the IP system on companies' performance, as measured by input and sales growth, as well as TFP.

### 5.1 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 and trademarks 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 48,924 observations on 7,721 firms, 19 per cent of which have gaps in their data of one to three years.[16]

Some sample 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 between 1991 and 2005. 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, with about 55 per cent of firms filing for trademark(s) between 1991 and 2005, and only 3 per cent filing for patent(s).

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 are in fairly low-tech sectors, with almost one third of the firms in the food and beverage sector, and a large number in apparel, wood products, and fabricated metal products. Employment-weighted, about 60 per cent of the firms are the low-tech sectors food, textiles, apparel, leather, wood, furniture and other manufacturing. These sectors are consumer good-intensive, so it is not that surprising that trademarks are much more important than patents for Chilean firms.

### 5.2 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 trademark and patent filings by these firms, and how these filings 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. Abud et al (2013) show that there are about 2,700 patent filings per year in this period in Chile, over 90 per cent of which are from non-residents, and about 29,000 trademark filings per year, less than 30 per cent of which are from non-residents. Figure 2 shows similar patterns for the ENIA firms: The number of filings from domestic ENIA firms is about 20 patents per year, so most of the resident patent filings in Chile are not from ENIA firms. In contrast to the patent filings, about 80 per cent of the trademark filings by ENIA firms are domestic, but again, they are a small fraction of the overall resident trademark filings.

[16] 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.

**Figure 2: Foreign-owned vs. domestic filings (1995-2005)**

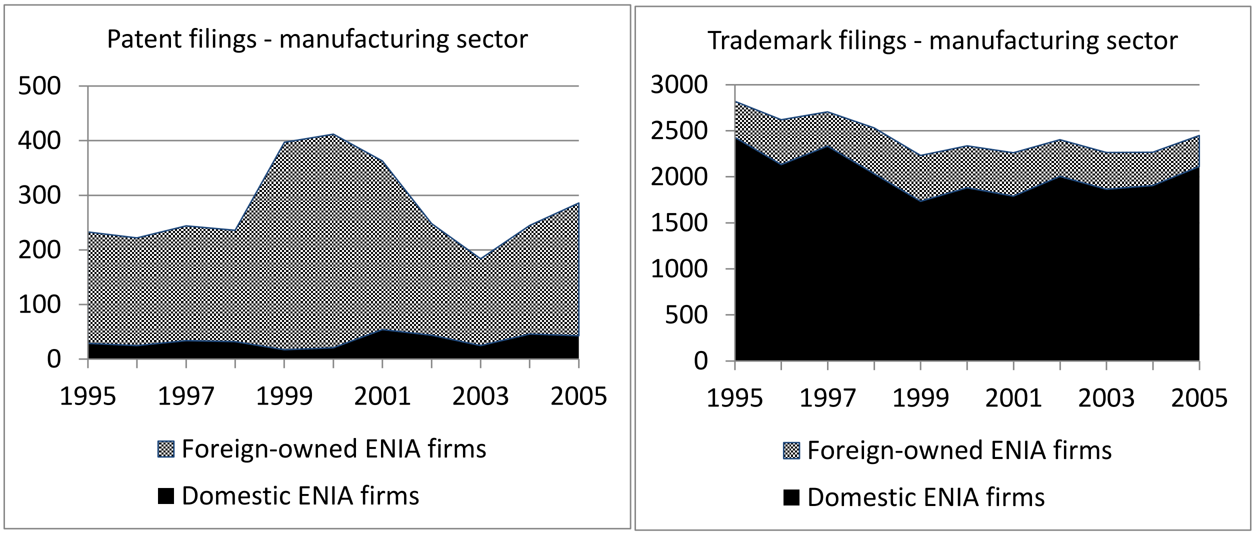



Table 2 shows the use of trademarks and patents by industrial sectors. In general, sectors that make high use of one kind of IP tend to also use the other (chemicals including pharmaceuticals, rubber and plastics, basic metals, and medical devices and precision instruments). Pharmaceuticals by itself 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. It is worth highlighting that there is an active domestic pharmaceutical industry in Chile. However, the existing evidence shows that nearly all patent filings in this industry are accounted for by foreign originator companies as domestic generics producers do not engage in new drug development during our period of analysis and instead focus on the production of generics and contract manufacturing of originator drugs (Abud et al., 2015). Instead, the evidence shows that domestic generic producers use the trademark system as they account for more than half of all trademark filings on pharmaceuticals (Abud et al., 2015).

We separate the firms into two groups: those that use one type of IP for the first time in 1995-2005, and those that were already using it when they entered the sample. The sectors with the largest share of old users of both patents and trademarks are chemicals and related products, and instruments, but the industry variations are not that large. Looking at the new users of patents and trademarks, the largest increases in patents (by share of firms) are in chemicals, rubber and plastics, motor vehicles, and basic metals. By shares, new users of trademarks are more equally distributed across industries than new users of patents.

**Table 2: Use of trademarks and patents by manufacturing sector firms**

| ISIC2 | Industry | Number of firms | Shares Old TM users | New TM users | Old patent users | New patent users |
|---|---|---|---|---|---|---|
| 15, 16 | food products and beverages, tobacco | 2,240 | 33.3% | 12.6% | 0.2% | 0.7% |
| 17 | textiles | 429 | 40.6% | 12.1% | 0.2% | 0.5% |
| 18 | wearing apparel; dressing and dyeing of fur | 551 | 42.8% | 10.2% | 0.0% | 0.2% |
| 19 | leather preparation & goods | 273 | 42.1% | 12.8% | 1.5% | 0.4% |
| 20 | wood, cork and straw products, ex furniture | 560 | 25.4% | 14.3% | 0.0% | 1.4% |
| 21 | paper and paper products | 194 | 40.2% | 12.9% | 1.0% | 2.1% |
| 22 | publishing, printing and media | 364 | 30.2% | 15.9% | 0.3% | 1.1% |
| 23, 24 | chemicals including coke & refined oil | 370 | 54.3% | 15.4% | 3.0% | 7.6% |
| 25 | rubber and plastics products | 463 | 37.6% | 17.9% | 1.5% | 5.4% |
| 26 | other non-metallic mineral products | 257 | 39.7% | 16.7% | 0.8% | 2.7% |
| 27 | basic metals | 136 | 40.4% | 18.4% | 2.9% | 8.1% |
| 28 | fabricated metal products | 656 | 31.3% | 12.8% | 0.3% | 1.4% |
| 29 | machinery and equipment | 418 | 31.8% | 12.7% | 0.2% | 1.9% |
| 30, 31, 32 | electrical machinery, computing machinery | 152 | 35.5% | 15.1% | 0.7% | 0.0% |
| 33 | medical, precision & optical instruments | 38 | 55.3% | 13.2% | 2.6% | 2.6% |
| 34 | motor vehicles, trailers and semi-trailers | 118 | 37.3% | 12.7% | 0.0% | 4.2% |
| 35 | other transport equipment | 60 | 35.0% | 13.3% | 1.7% | 0.0% |
| 36 | furniture; manufacturing n.e.c. | 442 | 37.3% | 9.7% | 0.2% | 0.7% |
| | **Total** | **7,721** | **2,775** | **1,028** | **44** | **132** |

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 (see for example Balasubramanian and Sivadasan 2011, Hall et al. 2013, Hall et al. 2014). We have some of the relevant data to explore whether and how these determinants operate in Chile. Unfortunately we do not have information on R&D, as that data is collected on the much smaller 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 at least one patent or trademark filing) or Poisson (for patent 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.[17]
- Dummy for a sole proprietorship.
- Dummy for an exporting firm.
- Dummy for location in the Santiago metro region.

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

- A set of 18 industry dummies.
- Year dummies.

Sample statistics for all the variables used in the regression below are shown in Appendix Tables B-4 (top panel) and B-5 (dummy variables). Later on, when we estimate TFP for these firms, we use the beginning of year capital stock in the regressions, because the theory on which the estimates are based treats capital as predetermined. It is also plausible that the effective capital available for the majority of the year is the beginning of year, not the end of year, measure. For this reason, the estimation sample is reduced by one year for each firm, from 48,924 observations to 41,675 observations.[18]

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-6 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. Table B-6 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 per cent, although only 2.8 per cent of the observations are foreign-owned, implying that the foreign-owned firms also tend to be bigger than the others.

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).
- Log of the share of sales in the 4-digit industry obtained by foreign-owned firms that year.
- A dummy for observations where the foreign firm share of sales in the industry was zero (about 30 per cent of the observations).

Table 3 displays probit and Poisson regressions that model the extensive and intensive use of trademarks as a function of these variables; Table 4 presents similar regressions for the use of patents. The dependent variable in the probit regressions is one if the firm had applied for a trademark or patent during the year of observation, whereas the dependent variable in the Poisson regressions is the count of trademarks or patents applied for that year. Larger firms and exporting firms are more likely to use either kind of IP protection. The use of trademarks increases with capital intensity, conditional on size and industry, as well as with industry concentration and firm's own market share. Firms located in the Santiago metro region are more likely to trademark and to patent.

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[18] We lose a few additional observations due to the need to have at least three years for each firm.

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 29 per cent and being a foreign firm effectively reduces that to zero, other things equal.

In these tables, 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, rubber and plastics, metals, 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 per cent 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, paper and paper products and machinery and equipment. The latter findings are consistent with the prediction that trademark use is more pronounced for consumer goods that have experience rather than search attributes. Comparing patent and trademark use across industries, chemicals seems to be the only industry that shows strong use of both IP instruments. This may suggest that the complementary relationship between branding and technological innovation found in high-income countries may well be weaker in a middle-income context.

Tables 3 and 4 also show the "intensive margin" regressions that use the number of trademark or patent applications filed. Controlling for firm size, firms in the Santiago region and firms with larger market shares apply for more trademarks. With the exception of chemicals, which applies for the highest number of trademarks per firm, most sectors apply for fewer trademarks than the food and beverage sector.

The average number of patent applications per firm per year is 0.06, a very small number. In spite of the rarity of patenting, there are a number of significant differences across firms in the number of patents they apply for in a year. Size, capital intensity, foreign ownership, public sector ownership, market share, and foreign sales in the firms' industry are strongly associated with the number of patents filed. However, due to the small sample of patentees, clustered standard errors in the Poisson regression tend to be quite large. Looking at the industry dummies, it is apparent that there may be substantial correlation between these and the other firm characteristics, as evidenced by large standard errors and large coefficients. So it is difficult to draw strong conclusions about patenting activity.

**Table 3**

Use of trademarks

| *Method of estimation:* | *Probit* | | | *Poisson* | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | *trademark app 1996-2005* | | | *N of trademark apps* | | |
| Log (employees) | 0.187 | (0.023) | *** | 0.574 | (0.081) | *** |
| Log (capital/employee) | 0.070 | (0.011) | *** | 0.062 | (0.043) | |
| D (foreign ownership) | -0.349 | (0.099) | *** | 0.325 | (0.246) | |
| D (public ownership) | -0.409 | (0.198) | * | -1.332 | (0.493) | ** |
| D (sole proprietorship) | 0.024 | (0.048) | | 0.085 | (0.216) | |
| D (exporter) | 0.129 | (0.041) | ** | 0.142 | (0.118) | |
| D (Santiago metro region) | 0.134 | (0.048) | ** | 0.282 | (0.140) | * |
| Log (market share) | 0.053 | (0.014) | *** | 0.206 | (0.050) | *** |
| Log (4-digit industry HHI) | 0.076 | (0.023) | ** | 0.145 | (0.073) | * |
| Log (foreign sales share in industry) | -0.011 | (0.008) | | 0.071 | (0.047) | |
| D (no foreign sales in industry) | 0.001 | (0.047) | | -0.537 | (0.179) | ** |
| textiles | -0.024 | (0.083) | | -0.574 | (0.210) | ** |
| wearing apparel; dressing and dyeing of fur | 0.169 | (0.077) | * | -0.248 | (0.242) | |
| leather preparation & goods | 0.141 | (0.098) | | -0.170 | (0.249) | |
| wood, cork and straw products, ex furniture | -0.317 | (0.081) | *** | -0.972 | (0.415) | * |
| paper and paper products | -0.212 | (0.119) | | -0.656 | (0.587) | |
| publishing, printing, recorded media | -0.183 | (0.095) | | -0.541 | (0.390) | |
| chemicals incl coke & refined oil | 0.389 | (0.088) | *** | 0.836 | (0.241) | *** |
| rubber and plastics products | 0.253 | (0.076) | *** | -0.115 | (0.249) | |
| other non-metallic mineral products | -0.007 | (0.104) | | -0.375 | (0.234) | |
| basic metals | 0.130 | (0.133) | | -0.838 | (0.344) | * |
| fabricated metal products | -0.139 | (0.070) | * | -1.078 | (0.185) | *** |
| machinery and equipment n.e.c. | -0.304 | (0.094) | ** | -1.165 | (0.268) | *** |
| electrical and electronic equipment | -0.186 | (0.136) | | -1.116 | (0.362) | ** |
| medical, precision & optical instruments | 0.045 | (0.232) | | -1.109 | (0.460) | * |
| motor vehicles, trailers and semi-trailers | -0.058 | (0.148) | | -0.626 | (0.331) | |
| other transport equipment | -0.195 | (0.206) | | -1.051 | (0.509) | * |
| furniture; manufacturing n.e.c. | -0.114 | (0.084) | | -0.105 | (0.383) | |
| Pseudo R-squared | 0.077 | | | | | |
| Chi-squared (df) | 629.9 (38) | | | 721.2 (38) | | |
| Number of observations | 48,924 | | | 48,924 | | |
| Number of firms | 7,721 | | | 7,721 | | |
| Mean (dep.var.) | 26.1% | | | 0.547 | | |

Year dummies included; robust standard errors clusterred on firm.

Excluded industry is food and beverage products

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

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

**Table 4**

Use of patents

| *Method of estimation:* | *Probit* | | | *Poisson* | | |
|---|---|---|---|---|---|---|
| *Dependent variable:* | *patent app this year* | | | *N of patent apps* | | |
| Log (employees) | 0.269 | (0.057) | *** | 0.840 | (0.169) | *** |
| Log (capital/employee) | 0.033 | (0.037) | | 0.257 | (0.110) | * |
| D (foreign ownership) | 0.322 | (0.140) | * | 2.711 | (0.453) | *** |
| D (public ownership) | -0.112 | (0.384) | | 1.776 | (0.300) | *** |
| D (sole proprietorship) | -0.243 | (0.201) | | 0.683 | (0.902) | |
| D (exporter) | 0.218 | (0.082) | ** | -0.025 | (0.436) | |
| D (Santiago metro region) | 0.192 | (0.085) | * | -0.408 | (0.224) | |
| Log (market share) | 0.069 | (0.043) | | 0.604 | (0.211) | ** |
| Log (4-digit industry HHI) | 0.015 | (0.059) | | 0.073 | (0.449) | |
| Log (foreign sales share in industry) | 0.048 | (0.026) | | 1.543 | (0.469) | *** |
| D (no foreign sales in industry) | -0.164 | (0.124) | | -3.213 | (0.829) | *** |
| textiles | -0.230 | (0.291) | | -1.741 | (0.846) | * |
| wearing apparel; dressing and dyeing of fur | -0.259 | (0.397) | | 1.978 | (1.410) | |
| leather preparation & goods | 0.049 | (0.337) | | 3.190 | (0.561) | *** |
| wood, cork and straw products, ex furniture | 0.260 | (0.227) | | -0.231 | (0.691) | *** |
| paper and paper products | 0.356 | (0.250) | | 3.383 | (0.466) | *** |
| publishing, printing, recorded media | 0.110 | (0.280) | | -3.143 | (0.722) | *** |
| chemicals incl coke & refined oil | 0.772 | (0.177) | *** | 1.494 | (0.467) | ** |
| rubber and plastics products | 0.989 | (0.177) | *** | -1.914 | (0.601) | ** |
| other non-metallic mineral products | 0.340 | (0.250) | | -1.372 | (0.916) | |
| basic metals | 0.858 | (0.246) | *** | -0.607 | (0.575) | |
| fabricated metal products | 0.468 | (0.206) | * | 0.775 | (0.661) | |
| machinery and equipment n.e.c. | 0.517 | (0.241) | * | 0.184 | (0.772) | |
| electrical and electronic equipment | | | | | | |
| medical, precision & optical instruments | 0.179 | (0.437) | | -4.030 | (1.156) | *** |
| motor vehicles, trailers and semi-trailers | 0.961 | (0.293) | * | -2.477 | (1.205) | * |
| other transport equipment | | | | | | |
| furniture; manufacturing n.e.c. | 0.331 | (0.295) | | 0.127 | (0.899) | |
| Pseudo R-squared | 0.259 | | | | | |
| Chi-squared (df) | 251.6 (36) | | | 1713.4 (36) | | |
| Number of observations | 47,538# | | | 47,538# | | |
| Number of firms | 7,509 | | | 7,509 | | |
| Mean (dep.var.) | 1.3% | | | 0.064 | | |

Year dummies included; robust standard errors clusterred on firm.

Excluded industry is food and beverage products

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

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

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

### 5.3 Impact of IP use on performance

We look at the relationship between IP use and performance in two ways: The first is a set of exploratory production function regressions where we include dummies for patent or trademark use as well as the firm descriptors used in the previous section. We estimate these production functions both in levels and within firm using fixed effects, neither of which completely control for feedback from productivity to patenting. Accordingly, we provide a second analysis that looks at the impact of first time IP use on firm performance. However, this approach also reveals that the adoption of an IP strategy is to some extent predicted by prior firm behavior.

#### 5.3.1 Descriptive results

Our descriptive results are shown in Tables 5 (trademarks) and 6 (patents). For trademarks, the regressions in levels reveal a clear positive association between productivity and applying for a trademark, one that persists over several years. The regression also shows that foreign firms, exporters and firms with a large market share are more productive, while sole proprietorships are less productive. The results for patenting are similar, although it takes slightly longer for patents to have an impact (column 3 of Table 6). Note that the other coefficients in the regression are roughly the same, whether we control for patenting or trademarks.

In Tables 5 and 6 we present two types of fixed effect estimates: column 4 contains results using 2-digit industry effects and columns 5-7 use firm fixed effects. Going within industry reduces both the trademark and patenting coefficients, but without losing much significance. In both cases, the use of IP is associated with about 10 per cent higher productivity. Within industry, firms in the Santiago metro region have slight higher productivity (about 4 per cent), while firms in 4-digit industries that have a larger share of foreign sales activity are less productive.

Turning to the firm fixed effect estimates, we observe the usual drop in coefficient size and significance, especially for the dummy variables that change little within firm (ownership and exporting status). Trademarking during the period is still slightly associated with higher productivity, but patenting is now entirely insignificant. This suggests that once individual firm-level productivity is controlled for, patenting firms are no different from the others.

**Table 5**

Production function estimates for trademark filing

| | OLS estimates | | | | OLS fixed effect estimates | | |
|---|---|---|---|---|---|---|---|
| *Dep. Variable* | *Log (sales per employee)* | | | | | | |
| D (trademark) | 0.102*** | 0.087*** | 0.062*** | 0.039*** | 0.011 | 0.012** | 0.014** |
| | (0.013) | (0.012) | (0.009) | (0.008) | (0.006) | (0.005) | (0.005) |
| 1-year lagged D (trademark) | | | 0.043*** | 0.025** | | | 0.010* |
| | | | (0.008) | (0.008) | | | (0.005) |
| 2-year lagged D (trademark) | | | 0.037*** | 0.021** | | | 0.008 |
| | | | (0.008) | (0.008) | | | (0.005) |
| Log Employment | 0.103*** | -0.041*** | -0.044*** | -0.132*** | -0.216*** | -0.509*** | -0.510*** |
| | (0.007) | (0.007) | (0.007) | (0.009) | (0.014) | (0.015) | (0.016) |
| Log Capital per employee | 0.112*** | 0.088*** | 0.088*** | 0.082*** | 0.022*** | 0.016*** | 0.016*** |
| | (0.006) | (0.006) | (0.006) | (0.005) | (0.005) | (0.004) | (0.004) |
| Log Materials per employee | 0.519*** | 0.470*** | 0.469*** | 0.412*** | 0.362*** | 0.223*** | 0.223*** |
| | (0.019) | (0.018) | (0.018) | (0.019) | (0.019) | (0.014) | (0.014) |
| D (foreign ownership) | | 0.263*** | 0.264*** | 0.232*** | | -0.007 | -0.008 |
| | | (0.045) | (0.045) | (0.039) | | (0.020) | (0.020) |
| D (public ownership) | | 0.096 | 0.102 | 0.102 | | 0.016 | 0.016 |
| | | (0.116) | (0.115) | (0.093) | | (0.043) | (0.043) |
| D (sole proprietorship) | | -0.100*** | -0.101*** | -0.091*** | | -0.007 | -0.008 |
| | | (0.013) | (0.013) | (0.012) | | (0.017) | (0.017) |
| D (exporter) | | 0.037** | 0.034* | 0.043*** | | 0.009 | 0.009 |
| | | (0.014) | (0.014) | (0.013) | | (0.008) | (0.008) |
| D (Santiago metro region) | | 0.016 | 0.015 | 0.029* | | 0.036*** | 0.036*** |
| | | (0.015) | (0.016) | (0.014) | | (0.008) | (0.008) |
| Log (market share) | | 0.127*** | 0.127*** | 0.210*** | | 0.414*** | 0.414*** |
| | | (0.006) | (0.006) | (0.009) | | (0.016) | (0.016) |
| Log (4-digit industry HHI) | | 0.003 | 0.002 | -0.010 | | 0.003 | 0.003 |
| | | (0.006) | (0.006) | (0.008) | | (0.009) | (0.009) |
| Log (foreign sales share in industry) | | 0.002 | 0.002 | -0.024*** | | -0.007*** | -0.007*** |
| | | (0.003) | (0.003) | (0.003) | | (0.001) | (0.001) |
| Firm-level fixed effects | No | No | No | No | Yes | Yes | Yes |
| Industry level fixed effects | No | No | No | Yes | Yes | Yes | Yes |
| R-squared | 0.742 | 0.780 | 0.780 | 0.809 | 0.471 | 0.675 | 0.675 |
| Standard error | 0.463 | 0.428 | 0.427 | 0.398 | 0.205 | 0.161 | 0.161 |

Robust standard errors clustered on firm.
33,482 observations on 6,564 firms.
All equations include a complete set of year dummies and a dummy variable that is equal to one if Log (foreign sales share in industry) is missing.
Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

**Table 6**

Production function estimates for patenting

| | OLS estimates | | | | OLS fixed effect estimates | | |
|---|---|---|---|---|---|---|---|
| *Dep. Variable* | *Log (sales per employee)* | | | | | | |
| D (patent) | 0.252*** | 0.132** | 0.055 | 0.008 | -0.015 | -0.028 | -0.029 |
| | (0.052) | (0.045) | (0.030) | (0.031) | (0.020) | (0.022) | (0.022) |
| 1-year lagged D (patent) | | | 0.078* | 0.036 | | | -0.030 |
| | | | (0.035) | (0.033) | | | (0.028) |
| 2-year lagged D (patent) | | | 0.131*** | 0.073* | | | 0.003 |
| | | | (0.035) | (0.035) | | | (0.023) |
| Log Employment | 0.107*** | -0.037*** | -0.038*** | -0.128*** | -0.216*** | -0.509*** | -0.509*** |
| | (0.007) | (0.007) | (0.007) | (0.009) | (0.014) | (0.016) | (0.016) |
| Log Capital per employee | 0.113*** | 0.089*** | 0.089*** | 0.083*** | 0.023*** | 0.016*** | 0.016*** |
| | (0.006) | (0.006) | (0.006) | (0.005) | (0.005) | (0.004) | (0.004) |
| Log Materials per employee | 0.519*** | 0.471*** | 0.471*** | 0.412*** | 0.362*** | 0.223*** | 0.223*** |
| | (0.019) | (0.018) | (0.018) | (0.019) | (0.019) | (0.014) | (0.014) |
| D (foreign ownership) | | 0.254*** | 0.244*** | 0.221*** | | -0.008 | -0.008 |
| | | (0.045) | (0.046) | (0.040) | | (0.020) | (0.020) |
| D (public ownership) | | 0.084 | 0.080 | 0.090 | | 0.016 | 0.016 |
| | | (0.115) | (0.113) | (0.091) | | (0.043) | (0.043) |
| D (sole proprietorship) | | -0.099*** | -0.099*** | -0.090*** | | -0.007 | -0.007 |
| | | (0.013) | (0.013) | (0.012) | | (0.017) | (0.017) |
| D (exporter) | | 0.039** | 0.039** | 0.045*** | | 0.009 | 0.009 |
| | | (0.014) | (0.014) | (0.013) | | (0.008) | (0.008) |
| D (Santiago metro region) | | 0.020 | 0.019 | 0.032* | | 0.036*** | 0.036*** |
| | | (0.016) | (0.016) | (0.014) | | (0.008) | (0.008) |
| Log (market share) | | 0.127*** | 0.127*** | 0.211*** | | 0.414*** | 0.414*** |
| | | (0.006) | (0.006) | (0.009) | | (0.016) | (0.016) |
| Log (4-digit industry HHI) | | 0.004 | 0.004 | -0.008 | | 0.003 | 0.003 |
| | | (0.006) | (0.006) | (0.008) | | (0.009) | (0.009) |
| Log (foreign sales share in industry) | | 0.002 | 0.002 | -0.024*** | | -0.007*** | -0.007*** |
| | | (0.003) | (0.003) | (0.003) | | (0.001) | (0.001) |
| Firm-level fixed effects | No | No | No | No | Yes | Yes | Yes |
| Industry level fixed effects | No | No | No | Yes | Yes | Yes | Yes |
| R-squared | 0.741 | 0.779 | 0.780 | 0.809 | 0.471 | 0.675 | 0.675 |
| Standard error | 0.464 | 0.428 | 0.428 | 0.399 | 0.205 | 0.161 | 0.161 |

Robust standard errors clustered on firm.

33,482 observations on 6,564 firms.

All equations include a complete set of year dummies and a dummy variable that is equal to one if Log (foreign sales share in industry) is missing.

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

### 5.3.2 First time IP use

To evaluate the impact of IP use on Chilean firms further, we compare key indicator variables such as the growth in sales, inputs, and productivity before and after the first use of trademarks or patents by the firm. Our analysis of first-time use of IP is in part motivated by the major change in Chile's IP system that occurred in 1991 which could have led to an uptake of IP use among manufacturing firms. Because we do not have pre-1991 data for the firms, we are unable to conduct a standard difference-in-differences analysis in response to this system-wide change. Instead we look at the impact of entry into use of the IP system at the individual firm level, recognizing that this "treatment" is not likely to be exogenous to the firm. Nevertheless, the results turn out to be informative about the evolution of IP use in the Chilean context.

In order to explore potential selection into first-time IP use, Table B-7 in the appendix reports the results of a hazard rate regression that estimates the probability of applying for a trademark or patent for the first time as a function of the same independent variables as those used in Tables 3 and 4. The explanatory power of the regression for trademarks is very weak and the only significant predictors of trademark adoption are firm size, and being in the chemicals or rubber and plastics sector. There is more explanatory power for patents, largely because they are highly sector specific, with firms in chemicals, rubber and plastics, metals, machinery, and autos much more likely to patent for the first time during the 1995-2005 period. The adoption of patents is also significantly related (positively) to firm size and to export status. Therefore, these results provide little evidence for selection into first-time IP use beyond firm size and industry, which we will account for directly in our regressions by including firm and industry fixed effects, and by estimating at the industry level.

Because patents and trademarks protect quite different things – brand names versus inventions – in what follows we analyze the association of each with firm performance 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:

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

where *i, t* indicate the firm and year, $\alpha_i$ and $\lambda_t$ 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, capital, materials, or TFP). The coefficient β measures the annual percentage increase in the dependent variable associated with trademark or patent use for the first time.

Equation (1) is recognizable as the multi-period generalization of the well-known difference-in-differences approach to estimation. When there are only two time periods, and first time IP use occurs only in the second, the ordinary least squares estimate of β is a consistent estimate of the impact of first time IP use on the dependent variables, provided that the underlying dependent variable trends for the IP users and non-users are parallel. This result remains true when there are more than two time periods, However, there is an additional complication in our case: rather than all units being "treated" at the same time, the "treatment" can occur in any of the time periods (11 in our data). This makes the estimator and its various usual robustness checks somewhat more complex, because it is not clear how to define the counterfactual treatment date for the controls. As observed earlier, an additional complication is that first time IP use is unlikely to be exogenous given the observed characteristics of the firms, including their pre-treatment trends, which will invalidate the causal interpretation of this estimator.

We take two approaches to deal with these problems. The first uses a descriptive regression to characterize the differing growth patterns of firms that begin using some form of IP during the

1995-2005 period and those that do not. The second is the propensity score method, which attempts to match treatment firms to similar control firms in order to mitigate some of the endogeneity concerns by conditioning on firm characteristics. For the first approach, define $T_i$ as the date that the $i$th firm uses IP for the first time, so that $t$-$T_i$ is the lag between the current time period and first-time IP use. The model we estimate is the following:

$$\log y_{it} = \alpha_i + \lambda_t + \delta_{t-T_i} I(IPuser_i) + \varepsilon_{it} \tag{2}$$

This model regresses the outcome variable for all firms on a firm fixed effect and year effects. For firms that are IP users by the end of the sample, it includes a set of dummies measured relative to the date that the firm first used IP. That is, these firms are allowed to have differing trends both before and after they adopt IP use. In the bottom halves of Tables 5 and 6 we present a summary version of the model in equation (2), where we use trends rather than lag dummies before and after first time IP use. In Figures 3 and 4, we show the lag dummies themselves.

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, new product introduction, and/or branding strategies. We also computed industry level TFP estimates that allow all the coefficients to differ across the 18 two-digit industries.

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 per cent 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 (for more detailed discussion see Eberhardt and Helmers, 2010):

$$\begin{aligned} \log r_{it} &= \alpha_t + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \\ \omega_{it} &= E[\omega_{it} \mid \omega_{it-1}] + \xi_{it} \end{aligned} \tag{3}$$

Where *r, k, l,* and *m* denote the logs of revenue, capital stock, labor, and intermediate inputs. $\omega_{it}$ is the current productivity level, observed by the firm, while $\varepsilon_{it}$ is the unobserved productivity shock. Olley-Pakes (OP) use current investment as a proxy for $\omega_{it}$, 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 OP 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 $\omega_{it}$ 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 $\xi_{it}$, 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 Table C-1. The OLS and ACF estimators are quite similar, whereas OP and LP show somewhat lower capital coefficients and LP also lower labor and materials coefficients. We prefer the ACF estimates for the reasons discussed above and because they require fewer assumptions to be consistent. In practice, all of these different 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, and we show only the results using the ACF estimator in the main text. We also computed TFP estimates using the ACF method industry-by-industry; these estimates are shown in Appendix Table C-2.

When estimating the difference-in-differences 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.[19] The results of estimation using equation (1) are shown below in Table 7 (for trademarks) and Table 8 (for patents). 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. We look at the changes in six firm variables: sales, employment, capital, materials, TFP, and TFP estimated for each industry separately. To explore potential heterogeneity across industries, Tables B-8 and B-9 in the appendix report results by industry. We discuss the results for trademarks and patents in the next two subsections. [20]

### 5.3.3 Trademarks

The top panel of Table 7 shows that although there is clear evidence that firms increase in size (by about 8 per cent annually) after their first trademark application, 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 look at this by including two trends: one for the "treated" firms before their first filing and one for the "treated" firms after their first filing. The inclusion of year dummies for all firms controls for overall growth in firms during the period. The first-time trademark users clearly have a trend growth before trademark adoption in sales, capital, materials, and TFP (but not in employment) that is higher than that of the controls. The coefficients on the trend after first-time use of trademarks suggest continued albeit slower growth. This means that the first use of trademarks is anticipated by sales, inputs, and TFP and their use does not increase the rate of growth. To probe the robustness of our results further, Table B-10 in the appendix shows results from a placebo regression. We randomly chose 25 per cent of firms in the estimation sample as first-time trademarking firms and then randomly chose their year in which they filed their first placebo trademark. The results in Table B-10 show no evidence for any association in the data between sales, input or TFP growth and the placebo trademark filing. This provides some reassurance that the observed associations in Table 7 are indeed driven by first-time trademark filings.

Table B-8 in the appendix shows the corresponding results by industry. We see that first-time use of trademarks is associated with sales growth only in food products and beverages, as well as furniture. First-time trademarking is also associated with employment growth in these two sectors as well as in chemicals which includes pharmaceuticals. In contrast, there is no evidence across industries that first-time trademark used is associated with TFP growth.

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

[20] The tables show 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 7: Impact of first trademark filing**

Difference-in-difference estimates for first-time Trademark filing

| *Dep. Variable* | *Growth after first time use of TMs/patents* | | | | | |
|---|---|---|---|---|---|---|
| | *Sales* | *Employment* | *Capital* | *Materials* | *TFP* | *TFP by ind@* |
| | Simple difference-in-difference | | | | | |
| D (after first TM) | 0.082*** | 0.071*** | 0.086** | 0.096*** | -0.010 | 0.000 |
| Robust s.e. | (0.020) | (0.015) | (0.031) | (0.026) | (0.011) | (0.013) |
| R-squared | 0.064 | 0.042 | 0.053 | 0.025 | 0.036 | 0.032 |
| Standard error | 0.333 | 0.255 | 0.535 | 0.490 | 0.252 | 0.264 |
| | Difference-in-difference estimates with trends | | | | | |
| Trend before first TM | 0.045*** | -0.002 | 0.060*** | 0.035*** | 0.021*** | 0.022*** |
| Robust s.e. | (0.005) | (0.004) | (0.008) | (0.006) | (0.002) | (0.003) |
| Trend after first TM | 0.025*** | -0.017*** | 0.040*** | 0.019*** | 0.018*** | 0.015*** |
| Robust s.e. | (0.002) | (0.001) | (0.003) | (0.003) | (0.001) | (0.001) |
| R-squared | 0.048 | 0.024 | 0.043 | 0.014 | 0.036 | 0.026 |
| Standard error | 0.335 | 0.258 | 0.538 | 0.493 | 0.252 | 0.265 |
| Observations (firms) | 31,103 (4,933) | | | | | |
| Number of first-timers | 1,015 | | | | | |
| Number of prior users% | 2,775 | | | | | |

Linear fixed firm effects estimation with standard errors clustered on firm.

All equations include a complete set of year dummies.

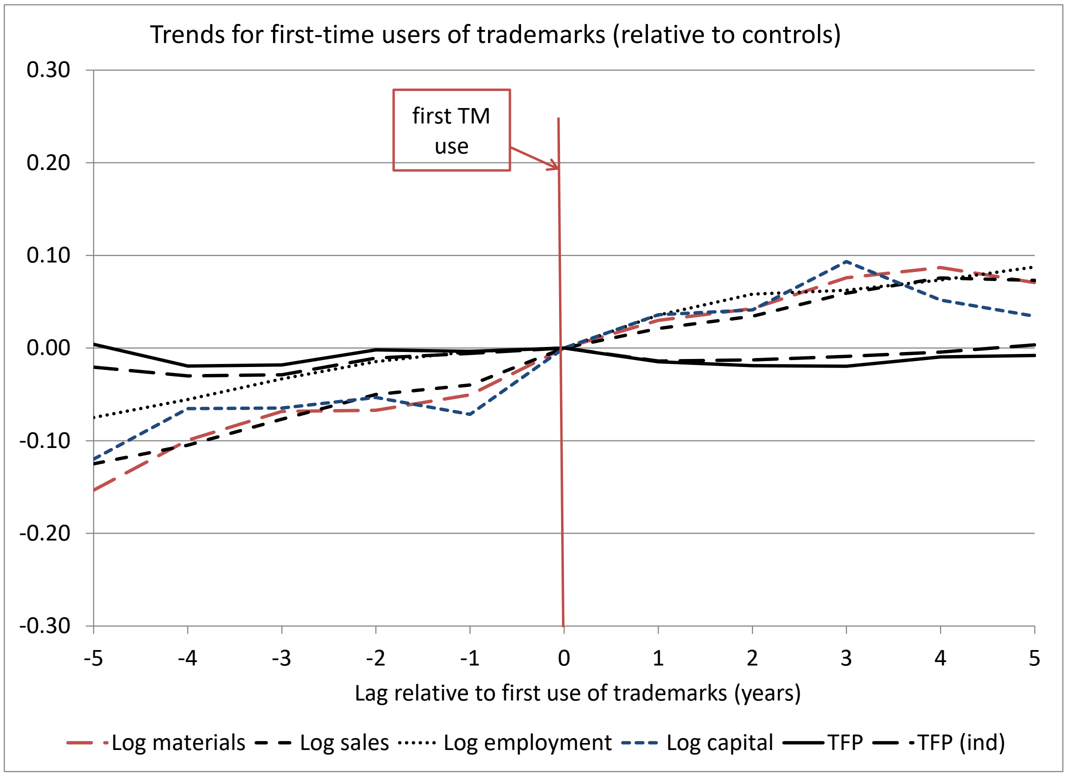
@ TFP estimated by two-digit industry using ACF estimator.

% 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 trends of the six variables 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 much. Sales and materials inputs track fairly closely, while employment grows smoothly and somewhat more slowly before first trademark use. Fixed capital is higher post-adoption, but has a less clear trend. Because the input variables grow in parallel with output, there is little visible impact on the average firm's productivity from first time trademark use; if anything, it falls slightly.

**Figure 3**




### 5.3.4 Patents

The results for patents, shown in Table 8 and Figure 4, are less clear because the relative rarity of patent use means that standard errors are rather large. The lack of patenting also posed a challenge for the sector-level analysis shown in appendix Table B-9.

The top panel in Table 8 suggests a positive effect of first-time patenting on sales growth. However, the bottom panel shows that there is strong growth before a firm files for a patent the first time and growth decreases afterwards. This again suggests that firms that file for a patent for the first time, do so when they already have been experiencing strong growth and patenting does not increase their growth rate. In Table 8, we also find a positive TFP trend pre- and post-first-time patenting. Yet, again there is no evidence that TFP growth increases after a firm's first patent filing. Table B-11 shows again results from placebo regressions where we randomly select treated firms and the year in which they filed their first placebo patents. Similar to the results for trademarks reported in Table B-10 we see no statistically significant results for the sales, TFP, or input growth specifications.

The sector-level results in Table B-9 show that there is no effect of first-time patenting on TFP growth in any of the manufacturing industries. There is some evidence of a positive association with sales growth in motor vehicles, rubber and plastics products, and food and beverages.

However, there is also a negative association with sales growth in furniture apparel and leather goods.

The results for patents in Figure 4 are also far more dispersed than in the case of trademarks: note that the scale has been chosen to be the same for Figures 3 and 4 to highlight the difference. Still, overall they are roughly equivalent to those for trademarks, with higher growth rates before the first patent use than after, and no significant impact on TFP. However, Figure 4 does show some differences: employment stops growing after the first patent application, and this together with a slight capital decline means that the TFP measures do grow, albeit not significantly more than prior to first patent use.[21]

**Table 8: Impact of first patent filing**

Difference-in-difference estimates for first-time Patent filing

| *Dep. Variable* | *Growth after first time use of TMs/patents* | | | | | |
|---|---|---|---|---|---|---|
| | *Sales* | *Employment* | *Capital* | *Materials* | *TFP* | *TFP by ind@* |
| Simple difference-in-difference | | | | | | |
| D (after first patent) | 0.180*** | 0.106 | -0.004 | 0.216*** | 0.016 | 0.033 |
| Robust s.e. | (0.051) | (0.055) | (0.077) | (0.060) | (0.028) | (0.030) |
| R-squared | 0.068 | 0.035 | 0.054 | 0.028 | 0.040 | 0.034 |
| Standard error | 0.333 | 0.265 | 0.517 | 0.476 | 0.245 | 0.259 |
| Difference-in-difference estimates with trends | | | | | | |
| Trend before first patent | 0.097*** | 0.031* | 0.078*** | 0.105*** | 0.018** | 0.017* |
| Robust s.e. | (0.013) | (0.013) | (0.019) | (0.017) | (0.006) | (0.007) |
| Trend after first patent | 0.030*** | -0.014*** | 0.040*** | 0.024*** | 0.019*** | 0.017*** |
| Robust s.e. | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) |
| R-squared | 0.057 | 0.018 | 0.040 | 0.020 | 0.040 | 0.030 |
| Standard error | 0.335 | 0.267 | 0.521 | 0.477 | 0.245 | 0.260 |
| Observations (firms) | 48,433 (7,656) | | | | | |
| Number of first-timers | 111 | | | | | |
| Number of prior users% | 44 | | | | | |

Linear fixed firm effects estimation with standard errors clustered on firm.

All equations include a complete set of year dummies.

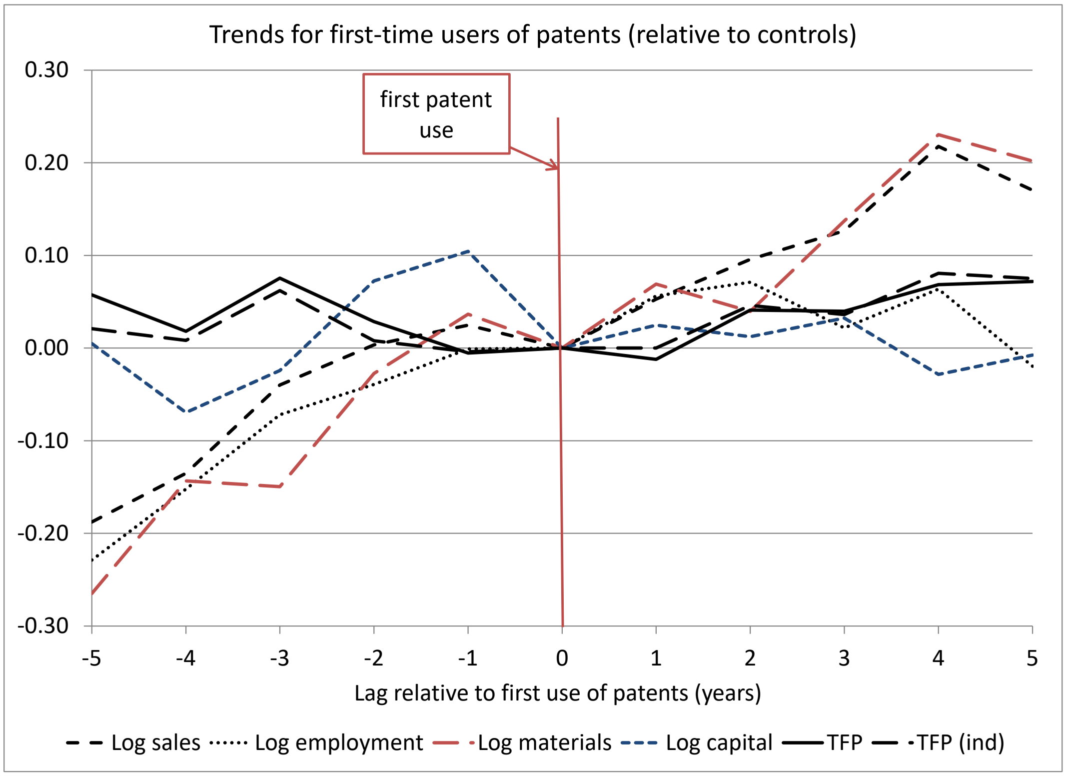
@ TFP estimated by two-digit industry using ACF estimator.

% These firms are not in the estimation sample.

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

[21] The sample plotted in Figure 4 is slightly different from the sample used for estimation in Table 8, as it is truncated at lags (-5, +5) due to the small number of observations at the longer lags. This explains the apparent inconsistency between the graph and the trends in Table 8 for TFP.

**Figure 4**




### 5.3.5 Treatment effect estimates using propensity score

The fact that firms entering into IP use appear to grow faster than others before filing for trademarks or patents implies that our difference-in-difference estimates do not have parallel trends. To investigate this further, we use a treatment effect estimator where the propensity to be treated includes a measure of pre-treatment growth. In this way, we are comparing firms that grew similarly before the potential treatment and asking whether their growth trajectory changed following entry into IP use. For this purpose, the outcome variables used are the average growth rate of sales, inputs, and TFP from the year of first trademark/patent filing to 2005.

Our estimation strategy is based on the propensity score method suggested by Rosenfeld and Rubin (1983). Abadie and Imbens (2006) provided consistency proofs and other large sample properties of this estimator. We define treatment as the first time a firm trademarks (or patents). The controls are all firms that have not yet trademarked (patented). We then estimate the propensity to file for a trademark (or patent) for the first time using a model similar to that in Tables 3 and 4. However we add to this model a measure of the growth rate of the outcome variable prior to the treatment, in order to control for the fact that treated firms tend to grow faster before. Results of this Probit estimation for trademarks and patents are shown in Appendix Table D-1, where we also show the resulting propensity score distributions for treated and control firms.

The results of estimating the average treatment effect (ATE) using propensity score matching are shown in Table 9, top panel for trademarks and bottom panel for patents. In general the differences between treated and control firms are small and insignificant. Exceptions are the growth of capital for firms that file for a trademark and the (negative) growth of materials for firms that file for a patent. The conclusion is that once we match firms on observables including their pre-treatment growth rates, there is little visible impact on subsequent growth or TFP from entry into IP use.[22]

**Table 9**

Propensity score estimates of the average treatment effect

| *Dep. Variable* | *Growth after first time use of TMs/patents* | | | | | |
|---|---|---|---|---|---|---|
| | *Sales* | *Employment* | *Capital* | *Materials* | *TFP* | *TFP by ind@* |
| | | | Trademarks | | | |
| ATE | 0.0116 | 0.0096 | 0.0207* | 0.0071 | 0.0058 | -0.0006 |
| Robust s.e. | (0.0073) | (0.0054) | (0.0088) | (0.0107) | (0.0060) | (0.0070) |
| Observations (treated) | 22,715 (1,002) | | | | | |
| | | | Patents | | | |
| ATE | -0.0066 | 0.0266 | -0.0157 | -0.0563** | -0.0045 | -0.0238 |
| Robust s.e. | (0.0235) | (0.0148) | (0.0202) | (0.0191) | (0.0053) | (0.0222) |
| Observations (treated) | 36,358 (91) | | | | | |

Weighted using propensity scores based on regressions in Appendix table D-1.

Samples are first time users of TMs/patents and all firms that have not yet used TMs/patents as controls.

@ TFP estimated by two-digit industry using ACF estimator.

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

### 5.3.6 Discussion

At face value, these findings suggest that firms experiencing 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. There is of course the concern that firms choose whether to use IP. Even though the results shown in Table B-7 provide little evidence for selection into IP use based on observable firm characteristics, there may still be time-varying correlated unobservables. Therefore we cannot rule out that firms could have done worse had they not used IP. However, the important observation here is that firms start using the IP system only after they have already been growing and their decision to use IP then does not improve their growth performance.

[22] We observe growth over varying number of years, depending on how close the entry is relative to 2005 or the exit date for the firm. The mean number of years over which growth is observed is three, probably long enough to see an impact if there is one.

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. That said, there is evidence for various developed economies that trademarks are in fact associated with improved firm performance, including employment and productivity (see Schautschick and Greenhalgh (2016) for a summary of this literature). Our descriptive results shown in Table 5 in fact suggest a positive association between trademark filings and productivity.

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 whether 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. Still, the lack of patenting by firms and the absence of any significant association between patenting and firm performance even in our descriptive regressions casts doubt on the role that patents have played in the development process of the Chilean manufacturing industry.

## 6. 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 as discussed in the introduction 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). There are also good reasons to think that trademark protection is more suitable for firms that may not be on the global technology frontier.

In this paper, we used a new comprehensive dataset for Chile that combines detailed firm-level information from the annual manufacturing census with the same firms' trademark and patent filings to analyze the use of IP by firms in Chile and its effect on outcomes, in particular growth and productivity.

Our results confirm that Chilean firms rely much more on the use of trademarks than patents even in the manufacturing sub-sample. 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 mirror those of high-income countries to a great extent, in the sense that similar variables predict its use. 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, as the growth tends to precede the first use of IP by a number of years. 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.

What do these results have to say about the role of the IP system in development? With respect to patents, it is difficult to argue that they have played much of a role in Chile's rapid economic growth, although the small number of firms that use them have been among the faster growing firms during the 1995-2005 period. In the case of trademarks, there is much more widespread use, and the firms using them have also grown rapidly before and after their first use. This suggests that the trademark system might play an important and so far underappreciated role in the development process of middle-income economies.

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# ONLINE APPENDIX

## 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 patent and trademark match success

| | Patents | | | | Trademarks | | | |
|---|---|---|---|---|---|---|---|---|
| *Year* | *Number of filings* | *% matched to ENIA* | *Number of applicants* | *% matched to ENIA* | *Number of filings* | *% matched to ENIA* | *Number of applicants* | *% matched to ENIA* |
| 1995 | 599 | 45.08 | 121 | 15.70 | 21,943 | 13.76 | 8,120 | 7.04 |
| 1996 | 771 | 39.30 | 147 | 18.37 | 21,687 | 12.97 | 7,826 | 7.10 |
| 1997 | 1,148 | 21.25 | 140 | 15.71 | 23,785 | 11.92 | 8,034 | 6.86 |
| 1998 | 1,244 | 19.37 | 156 | 18.59 | 20,646 | 12.81 | 7,546 | 6.73 |
| 1999 | 1,221 | 35.54 | 141 | 14.89 | 21,071 | 11.20 | 7,519 | 6.26 |
| 2000 | 1,320 | 34.55 | 152 | 13.82 | 25,774 | 10.02 | 8,234 | 5.39 |
| 2001 | 1,123 | 32.41 | 155 | 12.90 | 23,793 | 10.06 | 7,924 | 5.48 |
| 2002 | 994 | 27.26 | 181 | 13.26 | 24,061 | 10.62 | 8,347 | 5.42 |
| 2003 | 932 | 19.85 | 161 | 16.77 | 23,712 | 9.97 | 8,370 | 5.23 |
| 2004 | 1,077 | 22.84 | 177 | 17.51 | 24,345 | 10.08 | 8,784 | 5.25 |
| 2005 | 1,196 | 24.33 | 182 | 18.13 | 27,607 | 9.60 | 9,634 | 5.26 |

**Table B-2**

ENIA-IP sample

| | *# firms* | *# using TMs* | *# using patents* | *# using TMs* | *# using patents* |
|---|---|---|---|---|---|
| *Year* | | *ever** | | *this year* | |
| 1995 | 4,455 | 2,440 | 140 | 537 | 18 |
| 1996 | 4,970 | 2,675 | 147 | 531 | 25 |
| 1997 | 4,796 | 2,603 | 142 | 521 | 22 |
| 1998 | 4,547 | 2,490 | 139 | 482 | 27 |
| 1999 | 4,338 | 2,362 | 130 | 437 | 18 |
| 2000 | 4,228 | 2,328 | 120 | 412 | 20 |
| 2001 | 4,064 | 2,222 | 116 | 391 | 18 |
| 2002 | 4,374 | 2,396 | 128 | 423 | 23 |
| 2003 | 4,357 | 2,376 | 124 | 406 | 25 |
| 2004 | 4,607 | 2,504 | 130 | 422 | 30 |
| 2005 | 4,188 | 2,334 | 129 | 447 | 30 |
| **Total** | **48,924** | **26,730** | **1,445** | | |

*ever means the firm used the IP protection method during the 1991-2005 period.

**Table B-3**

Sectoral distribution of ENIA-IP sample

| *ISIC2* | *Industry* | *# obs* | *# firms* | *Share* | *Emp wtd** | *Share* |
|---|---|---|---|---|---|---|
| 15, 16 | food products and beverages, tobacco | 14,295 | 2,240 | 29.0% | 204.15 | 34.0% |
| 17 | textiles | 2,859 | 429 | 5.6% | 21.62 | 3.6% |
| 18 | wearing apparel; dressing and dyeing of fur | 3,179 | 551 | 7.1% | 30.04 | 5.0% |
| 19 | leather preparation & goods | 1,757 | 273 | 3.5% | 17.70 | 3.0% |
| 20 | wood, cork and straw products, ex furniture | 3,343 | 560 | 7.3% | 60.43 | 10.1% |
| 21 | paper and paper products | 1,286 | 194 | 2.5% | 18.14 | 3.0% |
| 22 | publishing, printing and reproduction of recorded media | 2,202 | 364 | 4.7% | 19.13 | 3.2% |
| 23, 24 | chemicals and chemical products incl coke & refined oil | 2,567 | 370 | 4.8% | 42.89 | 7.1% |
| 25 | rubber and plastics products | 3,146 | 463 | 6.0% | 29.16 | 4.9% |
| 26 | other non-metallic mineral products | 1,686 | 257 | 3.3% | 20.44 | 3.4% |
| 27 | basic metals | 918 | 136 | 1.8% | 36.05 | 6.0% |
| 28 | fabricated metal products, except machinery & equipment | 3,997 | 656 | 8.5% | 38.06 | 6.3% |
| 29 | machinery and equipment n.e.c. | 2,618 | 418 | 5.4% | 19.13 | 3.2% |
| 30, 31, 32 | electrical machinery and apparatus, comp. machinery | 989 | 152 | 2.0% | 6.78 | 1.1% |
| 33 | medical, precision & optical instruments, watches & clocks | 292 | 38 | 0.5% | 1.96 | 0.3% |
| 34 | motor vehicles, trailers and semi-trailers | 799 | 118 | 1.5% | 5.20 | 0.9% |
| 35 | other transport equipment | 397 | 60 | 0.8% | 6.84 | 1.1% |
| 36 | furniture; manufacturing n.e.c. | 2,594 | 442 | 5.7% | 22.17 | 3.7% |
| | **Total** | **48,924** | **7,721** | | **599.88** | |

* weighted by 1000s of employees in the last year of data

## Table B-4

Simple statistics for the estimation samples

| | *mean** | *sd* | *median* | *p25* | *p75* | *min* | *max* |
|---|---|---|---|---|---|---|---|
| All: 48,924 observations on 7,721 firms. | | | | | | | |
| Number of employees (1000s) | 0.038 | 1.074 | 0.030 | 0.017 | 0.067 | 0.002 | 9.187 |
| Sales per employee (1000s of pesos) | 16440.2 | 0.908 | 14552.0 | 9080.7 | 26923.1 | 312.445 | 3,043,534 |
| BOY capital per employee (1000s of pesos) | 3601.6 | 1.550 | 3955.1 | 1487.1 | 9658.9 | 0.05882 | 4,528,041 |
| Materials per employee (1000s of pesos) | 5554.2 | 1.239 | 5197.9 | 2884.4 | 10909.1 | 0.00524 | 2,306,473 |
| Firm market share | 0.003 | 1.939 | 0.002 | 0.001 | 0.011 | 0.000 | 1.000 |
| 4-digit industry Herfindahl | 853 | 0.927 | 765 | 444 | 1786 | 143 | 10000 |
| 4-digit Ind share - sales by foreign firms # | 0.057 | 1.652 | 0.092 | 0.024 | 0.182 | 0.0004 | 1.000 |
| N of trademark apps | 0.547 | 4.106 | 0 | 0 | 0 | 0 | 210 |
| N of patent apps | 0.064 | 2.173 | 0 | 0 | 0 | 0 | 176 |
| With 3+ years of data: 33,482 observations on 6,564 firms. | | | | | | | |
| Number of employees (1000s) | 0.039 | 1.101 | 0.030 | 0.017 | 0.071 | 0.003 | 9.187 |
| Sales per employee (1000s of pesos) | 17644.2 | 0.912 | 15544.4 | 9686.4 | 28879.0 | 338.222 | 3,043,534 |
| BOY capital per employee (1000s of pesos) | 4253.5 | 1.492 | 4689.8 | 1770.8 | 11014.6 | 0.28571 | 4,528,041 |
| Materials per employee (1000s of pesos) | 5930.9 | 1.208 | 5439.4 | 3008.9 | 11650.0 | 0.00524 | 2,306,473 |
| Firm market share | 0.003 | 1.968 | 0.002 | 0.001 | 0.013 | 0.000 | 1.000 |
| 4-digit industry Herfindahl | 899 | 0.906 | 829 | 449 | 1816 | 168 | 10000 |
| 4-digit Ind share - sales by foreign firms # | 0.057 | 1.662 | 0.088 | 0.024 | 0.196 | 0.0004 | 1.000 |
| N of trademark apps | 0.579 | 4.213 | 0 | 0 | 0 | 0 | 184 |
| N of patent apps | 0.076 | 2.471 | 0 | 0 | 0 | 0 | 176 |

* Geometric mean for the first 7 variables.

\# Statistics for nonzero shares only, 34,270 and 23,146 observations respectively.

## Table B-5

Simple statistics for the dummy variables

| | *All* | *3+ years of data* |
|---|---|---|
| D (foreign ownership) | 2.7% | 2.7% |
| D (public ownership) | 0.6% | 0.4% |
| D (sole proprietorship) | 16.7% | 16.3% |
| D (exporter) | 20.6% | 21.2% |
| D (Santiago metro region) | 4.3% | 5.7% |
| D (no foreign firm sales in industry) | 30.0% | 30.9% |
| D (ever applied for trademark) | 26.0% | 32.1% |
| D (ever applied for patent) | 1.3% | 1.7% |
| D (trademark app in current year) | 10.2% | 10.5% |
| D (first time trademark user 1996-2005) | 9.4% | 12.9% |
| D (prior trademark user on entry) | 36.2% | 36.3% |
| D (patent app in current year) | 0.5% | 0.6% |
| D (first time patent user 1996-2005) | 1.3% | 1.7% |
| D (prior patent user on entry) | 0.7% | 0.7% |
| Observations | 48,924 | 33,482 |
| Firms | 7,721 | 6,564 |

## Table B-6

4-digit industry characteristics by 2-digit industry

| *Industry* | *All* | *Mean HHI* | *HHI>2500* | *Share with HHI>2500* | *Share foreign-owned sales* |
|---|---|---|---|---|---|
| food products and beverages, tobacco | 164 | 2643 | 64 | 39.0% | 11.7% |
| textiles | 73 | 1416 | 15 | 20.5% | 5.3% |
| wearing apparel; dressing and dyeing of fur | 12 | 889 | 0 | 0.0% | 1.2% |
| leather preparation & goods | 35 | 1343 | 4 | 11.4% | 1.0% |
| wood, cork and straw products, ex furniture | 55 | 1885 | 10 | 18.2% | 7.0% |
| paper and paper products | 33 | 2026 | 11 | 33.3% | 13.6% |
| publishing, printing & reproduction of recorded media | 64 | 3668 | 36 | 56.3% | 25.4% |
| chemicals and chemical products incl coke & refined oil | 105 | 3320 | 55 | 52.4% | 24.7% |
| rubber and plastics products | 31 | 3067 | 21 | 67.7% | 39.5% |
| other non-metallic mineral products | 88 | 3238 | 53 | 60.2% | 7.3% |
| basic metals | 22 | 3176 | 18 | 81.8% | 9.6% |
| fabricated metal products, except machinery & eq | 86 | 2699 | 31 | 36.0% | 3.9% |
| machinery and equipment n.e.c. | 144 | 2572 | 52 | 36.1% | 2.6% |
| electrical machinery and apparatus, comp. machinery | 95 | 3662 | 51 | 53.7% | 7.7% |
| medical, precision & optical inst, watches & clocks | 47 | 4607 | 37 | 78.7% | 35.4% |
| motor vehicles, trailers and semi-trailers | 33 | 4175 | 13 | 39.4% | 15.9% |
| other transport equipment | 45 | 4817 | 37 | 82.2% | 2.0% |
| furniture; manufacturing n.e.c. | 64 | 3205 | 34 | 53.1% | 1.8% |
| **Total** | **1,196** | **2947** | **542** | **45.3%** | **11.1%** |

The table shows the number of 4-digit industries in each of our industry classifications, and the number that are concentrated (HHI>2500).

**Table B-7**

## Hazard rate estimation for First Use of IP

| *Dependent variable is time until first use of* | *Trademark* | | *Patent#* | |
|---|---|---|---|---|
| Log (employees) | 0.164*** | (0.049) | 0.378* | (0.155) |
| Log (capital/employee) | 0.055* | (0.023) | 0.019 | (0.096) |
| D (foreign ownership) | -0.264 | (0.201) | 0.249 | (0.355) |
| D (public ownership) | -0.330 | (0.402) | -0.567 | (1.138) |
| D (sole proprietorship) | -0.010 | (0.095) | -0.618 | (0.597) |
| D (exporter) | 0.100 | (0.097) | 0.605* | (0.247) |
| D (Santiago metro region) | -0.002 | (0.172) | -0.009 | (0.334) |
| Log (market share) | 0.011 | (0.029) | 0.184 | (0.119) |
| Log (4-digit industry HHI) | 0.029 | (0.047) | -0.035 | (0.144) |
| Log (foreign sales share in industry) | -0.015 | (0.028) | 0.072 | (0.102) |
| D (no foreign sales in industry) | 0.077 | (0.117) | 0.107 | (0.372) |
| textiles | -0.056 | (0.171) | -0.481 | (0.766) |
| wearing apparel; dressing and dyeing of fur | 0.099 | (0.172) | -0.637 | (1.050) |
| leather preparation & goods | 0.129 | (0.187) | -0.768 | (1.051) |
| wood, cork and straw products, ex furniture | -0.083 | (0.142) | 0.949* | (0.480) |
| paper and paper products | -0.153 | (0.235) | 0.698 | (0.657) |
| publishing, printing, recorded media | 0.127 | (0.161) | 0.027 | (0.781) |
| chemicals incl coke & refined oil | 0.370* | (0.169) | 1.325** | (0.405) |
| rubber and plastics products | 0.327* | (0.130) | 2.142*** | (0.384) |
| other non-metallic mineral products | 0.233 | (0.185) | 0.882 | (0.541) |
| basic metals | 0.381 | (0.217) | 1.398* | (0.551) |
| fabricated metal products | 0.040 | (0.129) | 1.177** | (0.452) |
| machinery and equipment n.e.c. | -0.092 | (0.178) | 1.075* | (0.543) |
| electrical and electronic equipment | 0.179 | (0.248) | | |
| medical, precision & optical instruments | 0.253 | (0.455) | 0.502 | (1.216) |
| motor vehicles, trailers and semi-trailers | 0.078 | (0.290) | 1.595** | (0.601) |
| other transport equipment | -0.032 | (0.363) | | |
| furniture; manufacturing n.e.c. | -0.052 | (0.172) | -0.069 | (0.776) |
| Pseudo R-squared | 0.008 | | 0.127 | |
| Chi-squared (df) | 124.8 (38) | | 249.4 (36) | |
| Number of observations | 23,037 | | 43,105 | |
| Number of firms | 4,946 | | 7,677 | |

Estimation method is Cox proportional hazards.

Robust standard errors clustered on firm are shown.

Year dummies included; Left out industry dummy is food and beverage products

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

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

Firms that are using trademarks and/or patents prior to 1995 excluded from estimation.

**Table B-8**

Difference-in-difference estimates of first-time trademark filing - by sector

| *Dep. Variable* | *Obs (firms)* | *Log Sales* | *Log Employ-ment* | *Log Capital* | *Log Materials* | *TFP* | *TFP by ind@* |
|---|---|---|---|---|---|---|---|
| All | 31,103 | 0.082*** | 0.071*** | 0.086** | 0.096*** | -0.010 | 0.000 |
| | (4,933) | (0.020) | (0.015) | (0.031) | (0.026) | (0.011) | (0.013) |
| food products and beverages, tobacco | 9,551 | 0.098** | 0.096*** | 0.129* | 0.125** | -0.026 | 0.032 |
| | (1,493) | (0.036) | (0.028) | (0.054) | (0.046) | (0.022) | (0.026) |
| textiles | 1,673 | 0.072 | 0.009 | 0.082 | 0.012 | 0.053 | 0.051 |
| | (255) | (0.102) | (0.067) | (0.119) | (0.108) | (0.057) | (0.073) |
| wearing apparel & leather goods | 2,791 | 0.009 | -0.052 | -0.159* | -0.012 | 0.056 | 0.023 |
| | (471) | (0.057) | (0.041) | (0.079) | (0.079) | (0.030) | (0.038) |
| wood, paper, cork and straw products | 3,337 | 0.049 | 0.041 | 0.053 | 0.135 | -0.048 | -0.044 |
| | (534) | (0.072) | (0.056) | (0.101) | (0.085) | (0.033) | (0.036) |
| publishing, printing and reproduction | 1,586 | -0.012 | 0.042 | 0.024 | 0.090 | -0.082 | -0.089 |
| | (254) | (0.076) | (0.057) | (0.143) | (0.081) | (0.047) | (0.048) |
| chemicals and chemical products | 1,165 | 0.150 | 0.176** | 0.384* | 0.115 | -0.031 | -0.049 |
| | (168) | (0.090) | (0.059) | (0.156) | (0.126) | (0.060) | (0.065) |
| rubber and plastics products | 1,909 | 0.027 | 0.086 | 0.109 | 0.105 | -0.080* | -0.079* |
| | (285) | (0.077) | (0.063) | (0.116) | (0.087) | (0.031) | (0.031) |
| other non-metallic mineral products | 982 | 0.187 | 0.113 | 0.153 | 0.140 | 0.045 | 0.031 |
| | (155) | (0.113) | (0.066) | (0.193) | (0.144) | (0.062) | (0.071) |
| basic & fabricated metal products | 3,278 | 0.061 | 0.041 | 0.112 | 0.062 | -0.003 | 0.016 |
| | (529) | (0.061) | (0.047) | (0.105) | (0.083) | (0.036) | (0.038) |
| machinery and equipment n.e.c. | 1,754 | 0.045 | 0.004 | 0.168 | 0.053 | -0.003 | 0.009 |
| | (284) | (0.087) | (0.057) | (0.111) | (0.110) | (0.045) | (0.073) |
| elec & comp machinery, instruments | 765 | -0.014 | 0.062 | -0.376* | -0.087 | 0.044 | -0.005 |
| | (115) | (0.076) | (0.073) | (0.160) | (0.097) | (0.051) | (0.050) |
| motor vehicles & other transport eq | 722 | 0.121 | 0.055 | -0.171 | 0.067 | 0.078 | 0.083 |
| | (113) | (0.110) | (0.071) | (0.156) | (0.141) | (0.057) | (0.066) |
| furniture; manufacturing n.e.c. | 1,590 | 0.214* | 0.219** | 0.109 | 0.137 | 0.030 | -0.029 |
| | (277) | (0.100) | (0.074) | (0.157) | (0.131) | (0.040) | (0.051) |

Linear fixed firm effects estimation with standard errors clustered on firm.

All equations include a complete set of year dummies.

Coefficient (s.e.) shown is for a variable = 1 following first time trademark use and =0 otherwise.

@ TFP estimated by two-digit industry using ACF estimator.

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

**Table B-9**

Difference-in-difference estimates of first-time patent filing - by sector

| *Dep. Variable* | *Obs (firms)* | *Log Sales* | *Log Employ-ment* | *Log Capital* | *Log Materials* | *TFP* | *TFP by ind@* |
|---|---|---|---|---|---|---|---|
| All | 48,433 | 0.180*** | 0.106 | -0.004 | 0.216*** | 0.016 | 0.033 |
| | (7,656) | (0.051) | (0.055) | (0.077) | (0.060) | (0.028) | (0.030) |
| food products and beverages, tobacco | 14,254 | 0.156* | 0.114 | 0.128 | 0.062 | 0.057 | 0.111 |
| | (2,234) | (0.070) | (0.113) | (0.189) | (0.185) | (0.070) | (0.063) |
| textiles | 2,855 | 0.416 | -0.158 | -0.064 | 0.176** | 0.400 | 0.382 |
| | (428) | (0.283) | (0.103) | (0.089) | (0.054) | (0.345) | (0.308) |
| wearing apparel & leather goods | 4,910 | -0.067* | 0.129*** | -1.014*** | -0.014 | -0.011 | 0.066*** |
| | (820) | (0.028) | (0.024) | (0.049) | (0.039) | (0.017) | (0.019) |
| wood, paper, cork and straw products | 4,599 | 0.209 | 0.228* | 0.010 | 0.227 | -0.017 | -0.052 |
| | (750) | (0.129) | (0.116) | (0.167) | (0.137) | (0.036) | (0.044) |
| publishing, printing and reproduction | 2,188 | -0.069 | -0.163 | 0.563 | -0.208*** | 0.057 | 0.137 |
| | (362) | (0.045) | (0.181) | (0.750) | (0.061) | (0.172) | (0.160) |
| chemicals and chemical products | 2,398 | 0.108 | 0.030 | 0.096 | 0.200 | -0.023 | -0.044 |
| | (350) | (0.118) | (0.142) | (0.175) | (0.144) | (0.063) | (0.074) |
| rubber and plastics products | 3,064 | 0.248* | 0.193 | 0.186 | 0.330** | -0.036 | -0.050 |
| | (452) | (0.116) | (0.104) | (0.130) | (0.106) | (0.069) | (0.068) |
| other non-metallic mineral products | 1,672 | -0.493 | -0.378 | -0.269 | -0.270 | -0.149* | -0.122 |
| | (254) | (0.259) | (0.204) | (0.142) | (0.345) | (0.075) | (0.100) |
| basic & fabricated metal products | 4,844 | 0.067 | 0.036 | -0.094 | 0.016 | 0.052 | 0.060 |
| | (783) | (0.076) | (0.129) | (0.168) | (0.080) | (0.092) | (0.084) |
| machinery and equipment n.e.c. | 2,607 | 0.135 | 0.105 | -0.869* | -0.014 | 0.186 | 0.279** |
| | (417) | (0.167) | (0.256) | (0.381) | (0.208) | (0.110) | (0.102) |
| elec & comp machinery, instruments | 1,274 | NA | NA | NA | NA | NA | NA |
| | (188) | | | | | | |
| motor vehicles & other transport eq | 1,185 | 0.587*** | 0.454 | 0.146 | 0.647*** | 0.019 | 0.036 |
| | (177) | (0.145) | (0.248) | (0.209) | (0.157) | (0.069) | (0.036) |
| furniture; manufacturing n.e.c. | 2,583 | -0.482** | -0.299* | -0.842* | -0.202 | -0.150 | -0.087 |
| | (441) | (0.175) | (0.145) | (0.331) | (0.188) | (0.079) | (0.135) |

Linear fixed firm effects estimation with standard errors clustered on firm.

All equations include a complete set of year dummies.

Coefficient (s.e.) shown is for a variable = 1 following first time patent use and =0 otherwise.

Greyed out estimates have too few observations after first time use+A5 for analysis.

@ TFP estimated by two-digit industry using ACF estimator.

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

**Table B-10**

Difference-in-difference placebo estimates for first-time Trademark filing

| *Dep. Variable* | *Log Sales* | *Log Employment* | *Log Capital* | *Log Materials* | *TFP* | *TFP by ind@* |
|---|---|---|---|---|---|---|
| D (after first TM) | 0.001 | -0.005 | 0.009 | 0.010 | -0.003 | 0.004 |
| Robust s.e. | (0.020) | (0.015) | (0.030) | (0.027) | (0.013) | (0.014) |
| R-squared | 0.063 | 0.039 | 0.052 | 0.025 | 0.037 | 0.032 |
| Standard error | 0.333 | 0.255 | 0.535 | 0.490 | 0.252 | 0.264 |

Difference-in-difference placebo estimates with trends

| *Dep. Variable* | *Log Sales* | *Log Employment* | *Log Capital* | *Log Materials* | *TFP* | *TFP by ind@* |
|---|---|---|---|---|---|---|
| Trend before first TM | 0.000 | -0.001 | -0.007 | 0.001 | 0.001 | -0.001 |
| Robust s.e. | (0.006) | (0.004) | (0.009) | (0.009) | (0.004) | (0.004) |
| Trend after first TM | 0.002 | 0.001 | 0.002 | 0.003 | -0.001 | 0.002 |
| Robust s.e. | (0.006) | (0.004) | (0.011) | (0.008) | (0.004) | (0.004) |
| R-squared | 0.063 | 0.039 | 0.052 | 0.025 | 0.037 | 0.032 |
| Standard error | 0.333 | 0.255 | 0.535 | 0.490 | 0.252 | 0.264 |
| Observations (firms) | | | 31,226 (4,946) | | | |
| Number of first-timers | | | 1,032 | | | |
| Number of prior users% | | | 2,780 | | | |

Linear fixed firm effects estimation with standard errors clustered on firm.
All equations include a complete set of year dummies.
@ TFP estimated by two-digit industry using ACF estimator.
% These firms are not in the estimation sample.
Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

**Table B-11**

Difference-in-difference placebo estimates for first-time Patent filing

| *Dep. Variable* | *Log Sales* | *Log Employment* | *Log Capital* | *Log Materials* | *TFP* | *TFP by ind@* |
|---|---|---|---|---|---|---|
| D (after first TM) | -0.014 | 0.009 | 0.015 | -0.002 | -0.018 | -0.017 |
| Robust s.e. | (0.021) | (0.016) | (0.032) | (0.029) | (0.014) | (0.015) |
| R-squared | 0.068 | 0.035 | 0.054 | 0.027 | 0.040 | 0.034 |
| Standard error | 0.333 | 0.265 | 0.516 | 0.476 | 0.245 | 0.259 |

Difference-in-difference placebo estimates with trends

| *Dep. Variable* | *Log Sales* | *Log Employment* | *Log Capital* | *Log Materials* | *TFP* | *TFP by ind@* |
|---|---|---|---|---|---|---|
| Trend before first TM | 0.008 | 0.003 | 0.011 | 0.009 | 0.001 | 0.003 |
| Robust s.e. | (0.006) | (0.005) | (0.009) | (0.007) | (0.003) | (0.004) |
| Trend after first TM | -0.005 | 0.002 | -0.011 | -0.006 | -0.001 | -0.002 |
| Robust s.e. | (0.007) | (0.005) | (0.010) | (0.008) | (0.004) | (0.005) |
| R-squared | 0.068 | 0.035 | 0.054 | 0.028 | 0.040 | 0.034 |
| Standard error | 0.333 | 0.265 | 0.516 | 0.476 | 0.245 | 0.259 |
| Observations (firms) | | | 48,433 (7,656) | | | |
| Number of first-timers | | | 111 | | | |
| Number of prior users% | | | 44 | | | |

Linear fixed firm effects estimation with standard errors clustered on firm.
All equations include a complete set of year dummies.
@ TFP estimated by two-digit industry using ACF estimator.
% These firms are not in the estimation sample.
Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

## Appendix C: TFP Estimates

**Table C-1**

Comparing TFP Estimation methods

Dep Var = Log(revenue)

| | *OLS* | *Olley-Pakes* | *Levinsohn-Petrin* | *ACF (investment)* | *ACF (materials)* |
|---|---|---|---|---|---|
| Log (capital stock) | 0.113*** | 0.025** | 0.072*** | 0.098*** | 0.084*** |
| | (0.006) | (0.014) | (0.007) | (0.002) | (0.005) |
| Log (employment) | 0.493*** | 0.461*** | 0.268*** | 0.539*** | 0.487*** |
| | (0.019) | (0.020) | (0.035) | (0.002) | (0.008) |
| Log (materials) | 0.501*** | 0.418*** | 0.341*** | 0.464*** | 0.601*** |
| | (0.021) | (0.017) | (0.008) | (0.002) | (0.009) |
| Scale coefficient | 1.107*** | 0.904*** | 0.681*** | 1.101** | 1.172*** |
| | (0.007) | (0.014) | (0.036) | (0.002) | (0.007) |
| P-value for CRS | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| Instruments | -- | -- | Capital, lagged capital, employment, & materials | Capital, lagged capital, employment, & materials | Capital, lagged capital, employment, & materials |

All equations include year dummies.

Standard errors are bootstrap with 50 draws.

Chilean manufacturing data, 48,924 observations on 7,721 firms, 1995-2005.

After allowing for lag variables, 39,549 observations used in estimation.

**Table C-2**

ACF estimates of the production function

| *Industry* | *15* | *17* | *18* | *19* | *20* | *21* | *22* | *24* | *25* |
|---|---|---|---|---|---|---|---|---|---|
| | *food & beverage* | *textiles* | *wearing apparel* | *leather* | *wood, cork, straw* | *paper* | *publishing & printing* | *chemicals* | *rubber & plastics* |
| Observations | 11,593 | 2,339 | 2,534 | 1423 | 2,652 | 1056 | 1,767 | 2106 | 2,576 |
| Firms | 2,214 | 442 | 544 | 271 | 549 | 194 | 360 | 363 | 456 |
| Log (capital stock) | 0.202 | 0.199 | 0.040 | 0.103 | 0.073 | 0.088 | 0.021 | 0.100 | 0.053 |
| | (0.018) | (0.036) | (0.210) | (0.076) | (0.026) | (0.051) | (0.013) | (0.048) | (0.007) |
| Log (materials) | 0.334 | 0.315 | 0.514 | 0.932 | 0.461 | 0.262 | 0.558 | 0.634 | 0.673 |
| | (0.026) | (0.115) | (3.133) | (0.260) | (0.080) | (0.112) | (0.118) | (0.287) | (0.031) |
| Log (employment) | -0.019 | 0.057 | 0.130 | 0.024 | 0.603 | 0.945 | 0.626 | 0.500 | 0.344 |
| | (0.051) | (0.094) | (3.111) | (0.317) | (0.156) | (0.291) | (0.181) | (0.398) | (0.044) |
| Scale coefficient | 0.517 | 0.571 | 0.684 | 1.059 | 1.137 | 1.295 | 1.205 | 1.234 | 1.070 |
| | (0.053) | (0.164) | (6.013) | (0.889) | (0.134) | (0.162) | (0.070) | (0.507) | (0.016) |
| P-value for CRS | 0.000 | 0.009 | 0.958 | 0.423 | 0.307 | 0.068 | 0.003 | 0.644 | 0.000 |

| | *26* | *27* | *28* | *29* | *31* | *33* | *34* | *35* | *36* |
|---|---|---|---|---|---|---|---|---|---|
| | *other non-metal prods* | *basic metals* | *fabricated metal* | *machinery & eq* | *elec & computing machinery* | *instruments* | *motor vehicles* | *other transport eq* | *furniture & mfg NEC* |
| Observations | 1372 | 756 | 3,214 | 2,093 | 804 | 241 | 648 | 320 | 2,055 |
| Firms | 253 | 133 | 648 | 411 | 151 | 38 | 116 | 60 | 433 |
| Log (capital stock) | 0.037 | 0.120 | 0.185 | 0.156 | 0.099 | -0.005 | 0.060 | 0.198 | 0.085 |
| | (0.026) | (0.107) | (0.029) | (0.037) | (0.031) | (0.068) | (0.056) | (0.090) | (0.033) |
| Log (materials) | 0.733 | 0.312 | 0.235 | 0.194 | 0.462 | 0.920 | 0.838 | 1.042 | 0.208 |
| | (0.135) | (0.303) | (0.069) | (0.203) | (0.117) | (0.321) | (0.281) | (0.636) | (0.576) |
| Log (employment) | 0.430 | 0.319 | 0.285 | -0.058 | 0.608 | 0.649 | 0.026 | -0.371 | 0.940 |
| | (0.236) | (0.276) | (0.189) | 0.377 | (0.129) | (0.455) | (0.470) | (0.893) | (0.748) |
| Scale coefficient | 1.200 | 0.751 | 0.705 | 0.292 | 1.169 | 1.564 | 0.924 | 0.869 | 1.233 |
| | (0.111) | (0.715) | (0.185) | (0.529) | (0.073) | (0.711) | (0.289) | (0.229) | (0.620) |
| P-value for CRS | 0.070 | 0.728 | 0.109 | 0.175 | 0.020 | 0.428 | 0.790 | 0.567 | 0.706 |

## Appendix D: Propensity score estimation

Table 9 in the body of the paper presents results estimated using a treatment effects model, where the control and treated observations are matched using propensity score weighting.[23] This appendix presents the regressions used to estimate the propensity scores and plots of the resulting distributions for the two sets of observations. The treatment in this case is the first year a firm files for trademarks or patents. Controls are firm-years that have not yet filed for a trademark or patent. We predict the probability of being treated using the variables included in Tables 3 and 4 (size, foreign, public, sole proprietorship, exporter, Santiago, market share, HHI in the industry, share foreign sales in the industry, and year and industry dummies).

Tables 7 and 8 together with Figures 3 and 4 suggested that the treated firms differed from the untreated in that they exhibit input and sales growth prior to treatment (applying for a trademark or patent). Accordingly we also included in the propensity score regression the growth in firm size (employment) prior to treatment. The results of these regressions are shown in Table D-1. As in similar regressions earlier in the paper, the key variables that predict entry into IP use are firm size, and being in the chemicals or rubber and plastics sectors. In addition, patenting is also predicted by being in metals, machinery, and the motor vehicles sector. It is less likely for sole proprietors.

Figures D-1 and D-2 show the distribution of the propensity scores for trademarks and patenting. For trademarks, it is easy to see that there is considerable overlap between treated and controls, so the average treatment effects should be well-estimated. For patents, things are a bit worse: a very large number of control observations have a low patenting probability, whereas there is clearly overlap for a small number of controls, but enough to identify the effect. This result is doubtless due to the fact that patenting is a rare event (only 91 firms enter into patenting during 1996-2005) and only a few sectors have significant patenting.

[23] We also estimated the models using nearest neighbor weighting, but the results were essentially the same, so we do not show them here.

**Table D-1**

Probit for new IP use - to generate propensity score

| Dependent variable | *New trademark applicant this year* | | | *New patent applicant this year* | | |
|---|---|---|---|---|---|---|
| Lagged log (employees) | 0.0052 | 0.0021 | ** | 0.0007 | 0.0002 | *** |
| Pre application growth rate of employment | 0.0182 | 0.0089 | ** | 0.0004 | 0.0006 | |
| D (foreign ownership) | -0.0081 | 0.0078 | | 0.0001 | 0.0005 | |
| D (public ownership) | -0.0227 | 0.0121 | | | | |
| D (sole proprietorship) | -0.0025 | 0.0037 | | -0.0004 | 0.0005 | * |
| D (exporter) | 0.0078 | 0.0047 | | 0.0006 | 0.0004 | |
| D (Santiago metro region) | -0.0031 | 0.0069 | | 0.0001 | 0.0005 | |
| Log (market share) | 0.0008 | 0.0012 | | 0.0001 | 0.0001 | |
| Log (4-digit industry HHI) | 0.0033 | 0.0020 | | -0.0001 | 0.0002 | |
| Log (foreign sales share in industry) | -0.0012 | 0.0012 | | 0.0001 | 0.0001 | |
| D (no foreign sales in industry) | 0.0044 | 0.0051 | | -0.0001 | 0.0005 | |
| textiles | -0.0018 | 0.0068 | | -0.0001 | 0.0007 | |
| wearing apparel; dressing and dyeing of fur | -0.0005 | 0.0071 | | | | |
| leather preparation & goods | 0.0007 | 0.0082 | | -0.0003 | 0.0008 | |
| wood, cork and straw products, ex furniture | -0.0056 | 0.0055 | | 0.0019 | 0.0014 | * |
| paper and paper products | -0.0050 | 0.0087 | | 0.0006 | 0.0013 | |
| publishing, printing, recorded media | 0.0053 | 0.0073 | | 0.0016 | 0.0018 | |
| chemicals incl coke & refined oil | 0.0201 | 0.0105 | ** | 0.0045 | 0.0022 | *** |
| rubber and plastics products | 0.0190 | 0.0073 | *** | 0.0063 | 0.0024 | *** |
| other non-metallic mineral products | 0.0095 | 0.0095 | | 0.0028 | 0.0021 | ** |
| basic metals | 0.0108 | 0.0125 | | 0.0059 | 0.0039 | *** |
| fabricated metal products | -0.0014 | 0.0053 | | 0.0020 | 0.0012 | ** |
| machinery and equipment n.e.c. | -0.0058 | 0.0067 | | 0.0031 | 0.0021 | ** |
| electrical and electronic equipment | 0.0021 | 0.0114 | | | | |
| medical, precision & optical instruments | 0.0014 | 0.0206 | | | | |
| motor vehicles, trailers and semi-trailers | -0.0003 | 0.0122 | | 0.0068 | 0.0046 | *** |
| other transport equipment | -0.0066 | 0.0132 | | | | |
| furniture; manufacturing n.e.c. | -0.0060 | 0.0064 | | 0.0011 | 0.0013 | |
| Pseudo R-squared | 0.011 | | | 0.134 | | |
| Chi-squared (df) | 86.8 (36) | | | 167.2 (31) | | |
| Number of observations | 22,715 | | | 36,358 | | |
| Number of firms | 4,920 | | | 6,840 | | |
| Mean (dep.var.) | 4.4% | | | 0.3% | | |

Year dummies included; robust standard errors clusterred on firm.
Excluded industry is food and beverage products
& DF/dx shown; for dummies change in probability from 0 to 1 is shown.
Estimates significant at the 10% (*) 5% (**) and 1% (***) levels respectively.

**Figure D-1**

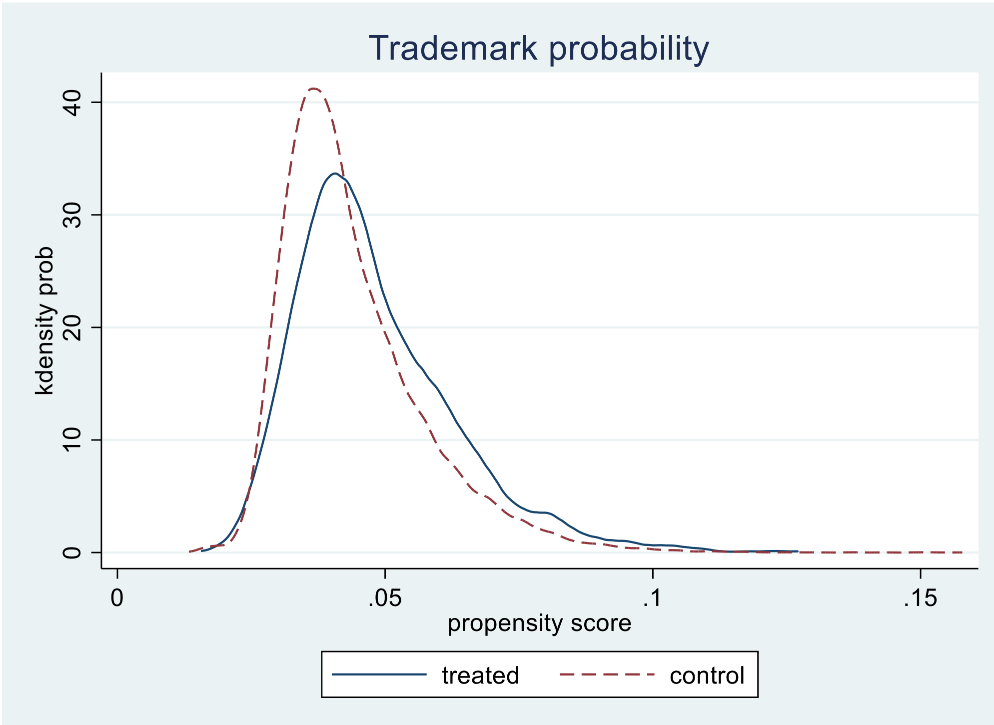


**Figure D-2**