Innovation and trade. Evidence from Italian manufacturing firms

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Abstract

Firms exposed to larger shares of foreign demand have greater incentives to innovate if market size matters for innovation. We test this hypothesis using Italian data from a representative sample of manufacturing firms. Our measure of innovation is the number of patent applications submitted by individual firms to the European Patent Office. Using the dynamics of world imports as an exogenous shock to exports classified by sector and province, we build an instrument for firm-level exports and find that passing from the 25th to the 75th percentile of the export distribution causes an increase of half a standard deviation in the probability of applying for a patent. This effect is driven by larger and more productive firms.

JEL classification: F10, O33

Keywords: Exports, Innovation, Patents, Firm Size, Productivity

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1 Introduction

Innovation is one of the key determinants of productivity and economic growth. A huge economic literature has shown that its determinants range from the human capital of the workforce to the quality and practices of management, from the financial structure to the relationship with external sources of financing, from industrial policies aimed at supporting innovation to, more in general, the institutional setting (e.g the regulatory frameworks of labor, financial and product markets).

Among the factors that are external to the firm, special attention has been dedicated to trade and to the different ways in which exposure to foreign trade can affect the innovation activity of a firm or, more in general, of an economy as a whole. At the aggregate level, several studies have shown how openness to trade can be a key determinant for technological progress (Coe and Helpman, 1995). More recently, micro-level advances, both theoretical and empirical, in the literature on international trade have revived the study of the link between trade and innovation. Starting from the seminal paper by Bernard and Jensen (1995) on US data, a large body of evidence has been developed for many advanced and emerging economies and has led, with a broad consensus, to the conclusion that exporting firms are larger, more productive and more innovative than non-exporters.

Three possible explanations can rationalize this evidence. The first concerns a self-selection mechanism. As Griliches (2000) points out, the effect of R&D investment on firm-level productivity growth is huge. In turn, the productivity level influences the exporting behavior of firms, as conceptualized by Melitz (2003), since only ex ante more productive firms choose to enter international markets. This implies that firms investing in R&D end up by being more competitive in international markets. The second explanation refers to the complementarity between market size and technological change. As Rodrik (1988) and Yeaple (2005) point out, the expected profits and therefore the incentive to invest in new technologies or products rise with the size of the final market; in this context, exporting activity can be seen as an enlargement of a firm's output market. In other words, complementarity implies that the size of export flows matters for innovation. The third explanation relates to the fact that trade flows facilitate international knowledge spillovers ((Coe and Helpman, 1995)) and, therefore, may contribute to the adoption of new technologies and the development of new, higher-quality products. This is known as the learning-by-exporting hypothesis,[1] whereby larger shares of exports result in better possibilities to acquire new technologies.

[1]There is a parallel learning-by-importing hypothesis according to which a firm can improve its efficiency thanks to the technology and quality embedded in imported intermediate inputs. Some recent papers in this field are: Amiti and Konings (2007), Goldberg et al. (2010), Khandelwal and Topalova (2011), Colantone and Rosario (2011).

In this paper, we test the complementarity hypothesis. We use Italian firm-level data and the European Patent Office (EPO) records to uncover the causal link that goes from international trade to incentives to innovate. We find that an increase in exports has a positive effect on the probability of a firm applying for a patent, which is our measure of innovation. Passing from the 25th to the 75th percentile of the export distribution increases the probability of patenting by 15% (half a standard deviation). Even if we do not perform a formal test, using the level of exports rather than an indicator of export participation as the measure of trade brings us closer to the complementarity hypothesis than to the learning-by-exporting hypothesis. To guide the interpretation of the results, we present a simple model whose main intuition is as follows: when firms face a fixed cost of innovation and the gains are proportional to market size, exports provide an incentive to invest. As a consequence only larger exporters innovate.

The empirical literature has struggled to find a convincing causal relationship between exports and productivity. Clerides et al. (1998) on Mexican and Moroccan firm-level data and Bernard and Jensen (1999) on US plant-level data find no effect of exporting on productivity. In a cross-country harmonized exercise, known as ISGEP (2007), some support for the learning-by-exporting hypothesis was found only for Italian firms, in particular smaller ones. Aw et al. (2011) estimate a structural model and find that productivity evolves depending on export and R&D spending. Their results suggest that investment in R&D has a greater impact on productivity than exports, and that exports have little impact on the decision to invest in R&D and the following productivity dynamics. Using data on Slovenian firms that start exporting, De Loecker (2007) finds, instead, that these firms become more productive after entering export markets and that their productivity gap with respect to domestic firms increases over time. With the aim of explicitly unveiling the learning channel, Crespi et al. (2008) show that, according to Community Innovation Survey data, exporters are more likely to report that they really do learn from foreign buyers; these firms then record higher productivity growth. Improving upon the identification strategy, Lileeva and Trefler (2010), using the implementation of the Canada-U.S. Free Trade Agreement shows that the labor productivity of Canadian firms increases as a consequence of U.S. tariff cuts and that this effect is stronger among ex-ante small and low productivity firms.

To overcome the difficulty of identifying a causal impact of exports on a measure like productivity, which can be affected by many other determinants, some scholars have taken a narrower view and focused on the relationship between trade and innovation. Salomon and Shaver (2005) find that the exporting activity of Spanish firms is associated with ex-post increases in patenting and product innovation; Salomon and Jin (2010) complement this result showing that the effect is stronger among technologically-advanced firms. On a sample of Irish and British firms, Girma et al. (2008) conclude that previous exporting experience enhances the R&D propensity of Irish firms, but not that of British ones. According to Damijan et al. (2010) exports increase the probability of process innovation and productivity growth of Slovenian firms. In a similar vein, Bustos (2011) shows that Argentinean firms responded to the MERCOSUR Free Trade Agreement by increasing both their export market participation and their spending on technology. She also finds that the impact of the exogenous reduction in tariffs on technological adoption is heterogeneous across firms, but with a different twist: it is stronger for firms that lie in the middle-upper range of the distribution in terms of size.

Our contribution to the literature is twofold. In the absence of trade liberalization episodes, as is typically the case for advanced countries, our first contribution is to deal with endogeneity concerns using an instrumental variable approach that relies on the exogenous developments of world imports. This is different from, likely more robust than, methodologies that either simply relate past exports to future innovation (as Salomon and Shaver, 2005; Salomon and Jin, 2010; Girma et al., 2008) or use propensity score-matching techniques to compare new exporters and non-exporters that ex ante have an equal probability of exporting (as Damijan et al., 2010). Moreover, we believe that the external validity of our IV approach is higher than that of unexpected trade liberalizations, which, as things stand, can only be experienced by a few developing countries and whose estimated impact is likely to depend on other institutional settings and therefore to be very country specific.

Our second contribution relates to the measure of innovation. In previous works, this is either a dummy variable based on firms' self-declared occurrence of product or process innovations over a given time span or the propensity or intensity of R&D activity. As compared to the latter method, which is a measure of innovative inputs, patents have the advantage of measuring a realized innovative output that can also confidently be related to product innovation. Compared with self-declared indicators of innovation, patents are less likely to suffer from measurement error and allow attention to be focused on innovations that are not marginal, but somehow important for the market. Some common drawbacks in the use of patent data in economics have been widely documented in the literature (Griliches, 1990).[2]

The paper is organized as follows. The next section presents a simple theory for exports and product innovation that guides the empirical part. Section 3 describes the identification strategy and how we solve the issue of

[2] First, patent counts do not reveal the economic value of patents, i.e. within the same industry it is not possible to distinguish between patents worth ten dollars and one billion dollars. Secondly, the use of patents varies across industries for reasons that might not be related to the propensity to innovate. Thirdly, it is not clear how much time passes between the time a firm pays the fixed costs to set up a research lab or to start a new innovative project and the time when a successful project gives rise to a patent application.

causality. Section 4 shows the dataset and section 5 presents the results of the estimates. Section 6 concludes.

2 Theoretical underpinnings

To convey the intuition of the economic mechanisms that drive the results in the empirical analysis we will use the predictions of a partial equilibrium version of Melitz (2003), as described in Helpman (2006). We enrich this general framework by adding the explicit possibility of innovation. Firms can invest in innovation upon paying a fixed cost. We think at patents as the outcome of such activity. We make two assumptions about the innovation process. First, innovation is characterized by uncertainty. This assumption is justified by the fact that in our data we observe that only a fraction of firms patent their innovation, generally the largest ones. Second, we assume patents to be an indicator of product innovation, and if firms produce a patent it can sell a new variety in the market.[3]

Consider a model with two countries: home and abroad (denoted by an $*$). Firms face a domestic isoelastic demand function $q(i) = p(i)^{-\sigma}A$ in a competitive monopolistic market. Foreign demand is given by $q^*(i) = p^*(i)^{-\sigma}A^*$. $\sigma > 1$ is the elasticity of substitution between any pair of varieties. A and A^* are measure of market size. $p(i)$ and $p^*(i)$ are prices charged by firms in the domestic and foreign market, the latter include the *ad valorem* tariff paid by firms to export. Firms are heterogenous in productivities φ' and the cost function is given by $(c/\varphi')q(i)$. We will focus on the static optimization problem, thus we assume A and A^* to be exogenous, and we normalize c to one.

As in the standard Melitz (2003) model, firms are allowed to export against the payment of a fixed cost F^X.[4] In addition we allow firms to undertake innovation activity. Innovation require to set up a research lab, for which firms have to pay an ex-ante uncertain fixed cost $F^I(1+\varepsilon_i)$, where ε_i is a random variable drawn from a uniform distribution with support $[0, 1]$. This formulation reflects the idea that some innovations are very ease to patent while others are extremely costly.[5]

[3] Unlike Yeaple (2005) and Bustos (2011) we have in mind a mechanism where trade liberalization pushes firms to increase profits by widening the range of products they supply. The advantage of this is twofold: on the theoretical side we can model the innovation step explicitly by building on the endogenous growth literature (Grossman and Helpman, 1991); on the empirical point of view it allows us to assess innovation using a measurable output rather than self-reported quantities or R&D input.

[4] In the following we assume that all firms in the markets have productivity above the survival threshold determined by the set-up fixed cost F^E.

[5] Implicitily we are assuming that cheap and costly innovation have the same probability. We make this assumption to keeps matters simple, but it is without loss of generality: any other distribution with cumulative density function increasing monotonically over the support will yield qualitatively the same results. For instance, all results would go

At the beginning of the period firms observe both their productivity and the innovation shock and only after they decide whether to invest or not. The output of the innovation activity is the patent (i.e. a product innovation). When firms succeed they introduce a new variety in the market and they increase their revenue.[6] Finally, since we observe in our data that it is much more likely that patenting firms are also exporters than vice versa, we will assume that $F^X < F^I$.

The profit function of a firm can be defined as a function of exporting and innovation activities: $\pi(E, I)$ with $E = \{0, 1\}$ and $I = \{0, 1\}$. We will have 4 different profit function.

$$\begin{aligned}
\pi(0,0) &= \varphi A \\
\pi(0,1) &= 2\varphi A - F^I(1+\varepsilon_i) \\
\pi(1,0) &= \varphi[A + \tau^{-\sigma}A^*] - F^X \\
\pi(1,1) &= 2\varphi[A + \tau^{-\sigma}A^*] - F^X - F^I(1+\varepsilon_i),
\end{aligned}$$

where φ is a transformation of productivity φ', namely, $\varphi \equiv [\varphi'(\sigma-1)]^{\sigma-1}\sigma^{\sigma}$.

By equating different profit functions, it is possible to identify the productivity cutoffs that identify the marginal firms that are indifferent between two alternative choices. We are interested in only two of the four endogenous thresholds that are defined by the equalization of the above profit conditions.[7] Following Melitz (2003) a firm is indifferent between exporting and selling only in the domestic market if $\pi(0,0) = \pi(1,0)$ which give the standard cutoff $\varphi^X = \frac{F^X}{\tau^{-\sigma}A^*}$. Analogously, exporting firms are indifferent between investing or not if $\pi(1,0) = \pi(1,1)$. The productivity cutoff will depend on the realization of the shocks and it is possible to identify two different thresholds. Suppose that the shock is equal to its minimum (i.e. $\varepsilon_i = 0$), by equating $\pi(1,0) = \pi(1,1)$ it is possible to derive $\underline{\varphi^I} = \dfrac{F^I}{(A + \tau^{-\sigma}A^*)}$. This cutoff corresponds to the minimum productivity level below which no firms will find profitable to invest even when the shock is equal to its minimum. Analogously, suppose that the shock is equal to its upper bound (i.e. $\varepsilon_i = 1$), again by equating the profit functions it is possible to identify $\overline{\varphi^I} = \dfrac{2F^I}{(A + \tau^{-\sigma}A^*)}$. This cutoff corresponds to the

through assuming that the random cost is drawn from a Pareto distribution, where cheap innovation would be much more likely than costly ones.

[6] We are assuming that all firms produce only one variety of the good and when they succeed in innovation they introduce a new variety. Moreover, we are assuming that no firms is sufficiently large to alter the equilibrium condition of the market when they introduce a new variety of good.

[7] Given $F^X < F^I$, we rule out the possibility that a domestic firm patent an innovation. A domestic firm would be indifferent between investing or not if $\pi(0,0) = \pi(0,1)$ which yields the cutoff $\varphi_0 = F^I/A$. Also we rule out the possibility that a domestic non innovating firm start exporting and innovating at once.

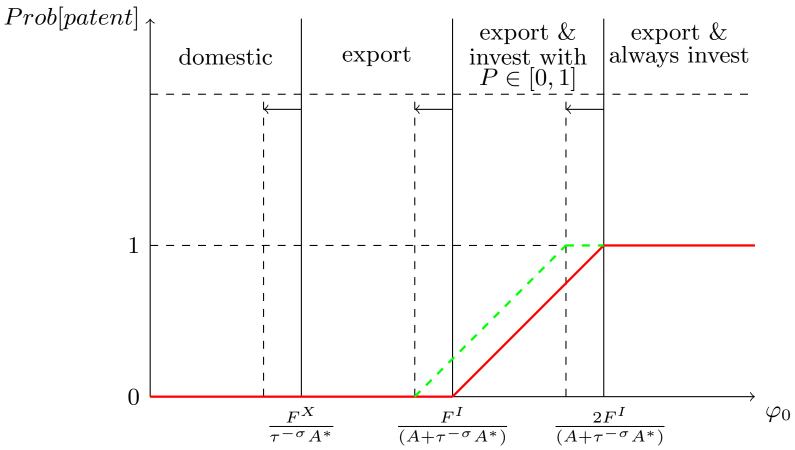
productivity level above which all firms will innovate irrespective of the realisation of the shock. For all firms with productivity between these two thresholds, the investment decision will depend on the realization of the shock. We can therefore write the ex-ante probability of innovation for a firm with intermediate levels of productivity as:

$$Prob[Patent] = Prob[\pi(1,1) \geq \pi(1,0) \mid \varphi \in (\underline{\varphi^I};\overline{\varphi^I})] \quad (1)$$

$$= Prob[\varepsilon_i \leq \frac{\varphi(A+\tau^{-\sigma}A^*)}{F^I} - 1 \mid \varphi \in (\underline{\varphi^I};\overline{\varphi^I})] \quad (2)$$

The probability of investing in innovation is increasing in productivity. This happens because the gains of innovation are proportional to the revenues while the costs are fixed; hence more productive firms are able to incur in higher fixed costs.

Figure 1: Export and investment decision



The probability of innovation as a function of productivity is represented by the red line in fig. 1. The different thresholds identify the productivity cutoffs which sort firms according to their exporting and innovation decision. There are four different categories: firms that sell only in the domestic market ($\varphi \leq \varphi^X$), firms that export without innovating ($\varphi \in (\varphi^X;\underline{\varphi^I})$), firms that export and invest in innovation with some probability ($\varphi \in (\underline{\varphi^I};\overline{\varphi^I})$) and firms that export and always invest in innovation ($\varphi \geq \overline{\varphi^I}$) .

Since $F^X < F^I$, and $\tau^{-\sigma}A* < \tau^{-\sigma}A * +A$ thresholds can be depicted as in figure 1 as long as $\frac{F^I}{F^X} \geq \frac{\tau^{-\sigma}A^* + A}{\tau^{-\sigma}A^*}$. The intuition is as follows: if the innovation cost is too low than all firms are willing to bear such cost of innovation since it provides them with extra-profits.

Finally, using this simple model we can show what happens to the probability of patenting when firms face either a decrease in trade cost ($\downarrow \tau$) or an increase in foreign market size ($\uparrow A^*$). Formally, consider the effect of a decrease in trade costs. All thresholds will move leftward in figure 1 while the probability of innovation will increase

$$\frac{\partial\, Prob[Patent]}{\partial\, \tau} < 0 \tag{3}$$

The green dashed line represent the new probability of innovation as a function of productivity. Figure 1 and eq. 2 show that an increase in trade (due to either shock) increases the probability of innovation along the intensive and the extensive margin. On the one hand, firms with intermediate productivity levels increase the probability of innovation. On the other hand, firms with productivity level just below $\underline{\varphi^I}$ start to innovate with a positive probability.

All these results suggest that the effect of a trade liberalization is likely to benefit larger and more productive firms. We will provide evidence about this prediction of the model in the following empirical exercise.

3 Empirical design

We want to assess the impact of the size of a firm's export flow on its innovation activity, that we measure through patenting. To this aim, we estimate the following equation:

$$D\{Patent\}_{isp}^{\{t+1,t+4\}} = \alpha + \alpha_s I_s + \alpha_t I_t + \alpha_p I_p + \beta X_i^t + \gamma Z_i^t + \varepsilon_{isp}, \tag{4}$$

where firms, sectors and provinces are indexed, respectively, by i, s and p, $D\{Patent\}_{isp}^{\{t+1,t+4\}}$ is a dummy variable taking value equal to 1 if the firm files the application for a patent in the following four years (between $t+1$ and $t+4$), I_s, I_t and I_p are, respectively, sector, year and province fixed effects, X_i is a variable which take values equal to $\ln(export)_i$ if $export_i > 0$ and 0 otherwise, Z_{is} is a set of firm-level controls.

$D\{Patent\}_{isp}^{\{t+1,t+4\}}$ is our proxy for innovation. Since patenting is a very lumpy activity due to both the uncertainty of the outcome of R&D activity and strategic considerations,[8] it makes little sense to proxy innovation with the probability of filing a patent application in a single year. We choose a four-year period for similarity with the median and average citation lag found both our sample and the NBER patent data, that is the time elapsing between when a certain patent is granted and the first time that patent is referred to in the application for a new patent. This wants to approximate the time lag between the start of a R&D activity (that is based on the

[8] A firm may decide not apply for a patent for an innovation it discovered in order to avoid the disclosure of specific knowledge required when filing a patent application (Reinganum, 1983, 1984, 1986).

current stock of knowledge) and the moment of a patent application (i.e. the new product is ready).

Since innovation is an activity with huge start-up costs and a steep learning curve, it makes a big difference whether the firm has already filed some patents in the past. For this reason we include among the firm-level controls Z_i a set of three dummies (i.e., dstock4y2, dstock4y3, and dstock4y4), which are, respectively, equal to 1 if the firm has filed between 1 and 5, between 6 and 10 or more than 10 patents in the past (i.e., between 1975 and $t-4$). The reference group is therefore comprised of firms that have filed zero patents up to $t-4$. As it will be clearer in the next section, our data are characterized by a relatively short time span and some attrition. This implies that we cannot use firm-level fixed effects (within estimator). We deem that the control for past patenting activity and past employment help us minimize the bias deriving from unobservable time-invariant firm-level features.

3.1 Causality

OLS estimation of equation (4) is potentially plagued by endogeneity issues. A first concern may derive by the presence of an omitted variable bias. Firm productivity or managerial capabilities, for example, can drive both the exporting and innovation decisions by firms, thus creating an upward bias in the OLS estimation. Another source of endogeneity is the presence of reverse causality due to self-selection mechanisms: consider, for example, the case of an innovative firm that has become productive enough to face the fixed cost of export. Then if this firm keeps on being relatively more innovative, then OLS would suffer from an upward bias; if, on the contrary, this firm, already close to the technological frontier, has lower incentives to invest in R&D and realize further innovations, then the bias would be downward.

To address these issues, we recur to instrumental variable (henceforth IV) estimation. As an instrument for firm-level exports we use the world sectoral imports. More in detail, the instrument is built in three steps. Ideally, we would like to attach to each firm's initial (back in time) level of exports the exogenous growth rate of world sectoral demand. Due, again, to the small panel dimension of our data we miss such information. We exploit the location of the firm and the availability of aggregate trade flows at the sector-province level to compute the exports of a representative firm in sector s and province p in 1995.[9]

As a first step, we compute the fictional export flow in each sector-province, by attaching the dynamic of world demand for sector s and province

[9] 1995 is the first year for which we have data on bilateral trade flows.

p to the exports of that sector-province cell in 1995.

$$\hat{X}^t_{sp} = \sum_c X^{1995}_{csp} \frac{M^t_{cs}}{M^{1995}_{cs}}, \quad t = 2001, \ldots, 2005. \tag{5}$$

where X^{1995}_{csp} represents the exports from sector s in province p to country c in 1995. M^t_{cs} and M^{1995}_{cs} are the imports of country c in sector s in, respectively, time t and 1995. $\hat{X}^t_{sp}$ is, therefore, the flow of exports from sector s and province p determined by a pull factor determined by the world demand in each sector. Cross-province variability is warranted by the fact that each sector-province had, in 1995, a different composition in terms of export markets and, therefore, have been exposed since then to different dynamic patterns of world demand. The exclusion restriction is based on the hypothesis that world demand in a certain sector is exogenous to the local exporting performance. This requires that each province is small enough not to influence the world demand in a certain sector. We deem this is guaranteed by the fact that the 1995 share of sectoral world exports for the largest Italian sector-province cell (the province of Milan for the production of electronic apparels) was 0.03 per cent. In other words, even the largest sector-province is negligible in comparison with world trade.

Then, as a second step, we normalize (5) by dividing the fictional export flow in the sector-province at time t by the number of firms in the same cell. That is: $\hat{X}^t_{isp} = \hat{X}^t_{sp}/N^{1995}_{sp}$.

Finally, we discretize $\hat{X}^t_{isp}$ by computing a set of mutually orthogonal dummies, that represent the quartile of the within-sector distribution of the fictional export flow. That is, let us call $q^n_{\Delta \ln \hat{X}_{st}}$ with $n = 25, 50, 75, 100$ the upper bound of respectively the 1st, the 2nd, the 3rd and the 4th quartile of the within sector distribution of $\hat{X}^t_{isp}$, then we build the following set of dummies:

$$D^1_{\ln \hat{X}^t_{ps}} = \begin{cases} 1 & \text{if } \ln \hat{X}^t_{ips} \leq q^{25}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$D^2_{\ln \hat{X}^t_{ips}} = \begin{cases} 1 & \text{if } q^{25}_{\ln \hat{X}^t_{ps}} < \ln \hat{X}^t_{ips} \leq q^{50}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$D^3_{\ln \hat{X}^t_{ps}} = \begin{cases} 1 & \text{if } q^{50}_{\ln \hat{X}^t_{ps}} < \ln \hat{X}^t_{ips} \leq q^{75}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$D^4_{\ln \hat{X}^t_{ips}} = \begin{cases} 1 & \text{if } \ln \hat{X}^t_{ips} > q^{75}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

The choice to discretize an otherwise continuous function is due to the possible presence of heterogeneous effects in the estimates. As the theoretical model shows, firms can be divided into three main groups according to the response of their exports to the world demand (see (Angrist and Pischke, 2009)): a group of *compliers*, whose exports expands in response to an increase in foreign demand, a group of *always-takers* which are always able to export a constant flow of regardless the level of the world demand, and a set of *never-takers* which never export. This implies that we are likely to face non-linearities in the first stage. In order to cope with this problem we discretize the instrument into dummy variables, with the aim to fit in the best way a non-linear relationship. For a similar approach see Lileeva and Trefler (2010) and Angrist and Imbens (1995).

In practical terms, our set of instruments is the subset:

$$\{D^2_{\ln \hat{X}^{t-1}_{ips}}, D^3_{\ln \hat{X}^{t-1}_{ips}}, D^4_{\ln \hat{X}^{t-1}_{ips}}\}$$

4 Data

The data used in this paper come from the merge of the "Indagine sulle imprese industriali e dei servizi" (Inquiry on industrial and service firms; henceforth INVIND), a survey run yearly since 1982 from the Bank of Italy, and PATSTAT, a commercial database compiled by the European Patent Office (EPO).

Up to 2001 INVIND only surveyed industrial firms with at least 50 employees. Since then INVIND has gone through some structural changes aimed at extending the sample: first starting in 2001 firms with at least 20 employees where added to the sample, with the aim of offering a better representation of the Italian productive system that is populated by a vast majority of small- and medium-sized firms; second, starting in 2002 services firms were also surveyed.

The INVIND questionnaires are submitted yearly to companies, and collect a wide range of information: nationality, location, age, sector of activity, ownership structure, employment (annual average), investment (realized and planned), sales (domestic and foreign), capacity utilization rate, indebtedness. The quality of the data is remarkably good, both for the thirty-year-experience in surveying firms and for the thorough statistical scrutiny performed by the Bank of Italy's statisticians.[10]

The PATSTAT database contains several information about patent applications presented by firms to EPO. The available information refers to the applicants' name, their addresses and the priority date of the application. Currently, PATSTAT covers the period 1975-2011, with completed and re-

[10]Among the papers based on SIM data, see Guiso and Parigi (1999) and Iranzo, Schivardi and Tosetti (2008). Data are available upon request to external researcher through the system BIRD `http://www.bancaditalia.it/statistiche/indcamp/sondaggio/bird`

liable data only up to 2009.[11] The merge between INVIND and PATSTAT is not an easy task. The main difficulty relies on the fact that patent applicants are recorded according to their name and that companies' names can vary for various reasons (uppercase vs. lowercase letters, complete vs. abbreviated names, different ways of abbreviating the same name, etc.), sometimes depending on the patent office which the patent application is filed to. Fortunately, this is not the first attempt at matching a patent database to other data and one can build on the several routines developed by the NBER Patent Data Project to harmonize names and to allow the matching of patent applicants to other databases. We use the matching between PATSTAT and Italian firms developed by Marin (2011), who —following the NBER routines— harmonizes names and then matches names recorded in PATSTAT to the harmonized names of the Italian firms in AIDA-*Bureau van Dijk* database. The last step consists in matching INVIND and AIDA-PATSTAT using tax codes as firms' identifiers.

Combining the PATSTAT data up to 2010 with the INVIND dataset of firms with more than 20 employees and restricting to the manufacturing sector,[12] our empirical analysis will be based on an open panel of 3085 firms over the period 2001-05. Among the firms included in our sample 599 hold at least one patent, 118 of those start to patent between 2001-05.

4.1 Basic statistics on patent in italian manufacturing

Some basic descriptive statistics from our sample are reported in Table 1. The average employment is 319 employees, the median is 103. Around 84% of firms export and the share of export over total sales is 33%.

Table 1: Summary Statistics

	Never patented		Patentees		Total	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Employment	194	440	793	1958	319	1007
Sales (mil. euros)	60.6	407.8	241.4	923.1	98.1	560.1
Export (mil. euros)	17.6	66.6	105.8	413.8	35.9	200.6
Export dummy	.812	.391	.965	.183	.844	.362
Export share	.293	.296	.461	.281	.328	.300

Source: INVIND and PATSTAT. Averages and standard deviations calculated over the period 2001-2005.

In the first two columns of table 1 we document basic differences between

[11] Usually, most recent data are gathered with a certain lag and updated in subsequent issues of the database.

[12] Both exports and product innovation are less relevant activities for most of services firms.

firms owning a patent and those that never patented. For each firm-year cell we define a dummy variable equal to 0 if a firm has never applied for a patent before and equal to 1 from the year of the first application. Patentees are about 4 times larger both in terms of employment and revenues, the share of exporting firms is 16 percentage point bigger and the export share is about 50% larger. The differences are smaller in magnitude compared to the ones documented using U.S. census data (Balasubramanian and Sivadasan (2011)), but our data cover only for firms with more than 20 employees.

Table 2: Share of Patentees by Sector

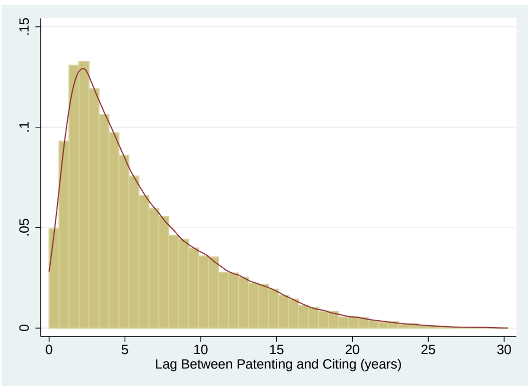
				Patentees	
	Number of firms	Share of patentees	R&D	share of empl.	share of revenue
15 Food and beverages	446	0.0493	370	0.3198	0.3457
16 Tobacco	6	0.1667	4	0.7757	0.9486
17 Textile	203	0.0542	191	0.1236	0.1058
18 Apparel	124	0.0242	365	0.1182	0.1666
19 Leather	133	0.0827	238	0.1208	0.1498
20 Timber	62	0.0806	55	0.2476	0.2050
21 Paper	86	0.1628	160	0.2175	0.1909
22 Printing and publ.	53	0.0755	37	0.5513	0.5571
23 Petroleum and coke	26	0.0769	404	0.1393	0.0081
24 Chemicals	184	0.3641	3261	0.6654	0.6792
25 Plastic	163	0.2638	478	0.3276	0.2718
26 Minerals	226	0.1062	252	0.3129	0.3125
27 Metals	126	0.1905	306	0.6945	0.6611
28 Metal products	283	0.1908	115	0.3751	0.3453
29 Machinery	421	0.4276	1458	0.7220	0.7405
30 Computer	12	0.2500	49290	0.9377	0.8926
31 Electrical equipment	115	0.3217	935	0.6772	0.6526
32 Telec. equipment	48	0.3333	4357	0.6065	0.7125
33 Medical and optical instr.	47	0.4043	1467	0.5894	0.6665
34 Cars and trucks	92	0.2935	22677	0.6995	0.7704
35 Other automotive	66	0.2424	11911	0.7102	0.7108
36 Furniture	163	0.0982	261	0.2267	0.2118
Total	3085	0.1942	2010	0.4559	0.4588

Source: INVIND and PATSTAT. The first column reports the number of firms, the second the share of patentees defined as firms that hold at least one patent. R&D is available only for years 2003-05 and for firms with more than 50 employees. Shares of employment and revenues in the last two columns are calculated as averages over the period 2001-2005.

In table 2 we document how patenting differs across sectors. In the first column we report the total number of firms per sectors while the second reports the average number of firms holding a patent. The last two columns report the share in total employment and total revenues of firms holding a patent. On average 19% of our firms hold at least one patent between 2001 and 2005 but they account for 45% of employment and revenues. There are a lot of differences across sectors: the share of patentees range from 42% in the machinery to the 2% in the apparel industry.

Our main measure of innovation is a dummy variable equal one if a firm apply for a patent in the next 4 years (see section 3), which corresponds to the to the median forward citation lag that we observe in our sample. The distribution of foreword citations is represented in fig. 2, the median citations lag is 4.83 years (the average is 6.3)

Figure 2: Lags between patenting and citing



Source: PATSTAT

Table 3 report sectoral averages on different measure of patenting activity. The first column reports the number of firms that apply for a patent in year t while the second the share of firms that apply for a patent in the following 4 years. The share of innovative firms passes from 7% when measured in a single year to 14% when using a 4 years time window. The table also documents a large heterogeneity across sectors. The distribution ranges from the zeros in sectors like "printing, publishing and reproduction" and "petroleum and coke products", to the very low numbers in the low-skilled intensive sectors of textiles, clothing, leather products and footwear, to large figures in the most innovative sectors like "machinery" and "electrical equipment"(where on average 33% of firms apply for a patent in the next 4 years). The third column of table 3 reports the total number of patent applications observed in our sample and its distribution across sectors. Finally, we compute a measure of patent stock, that proxies for the pre-existing knowledge of the firm, using the perpetual inventory method with an annual depreciation rate of 15% following Hall et al. (2005). The last column reports the average depreciated patent stock across firms.

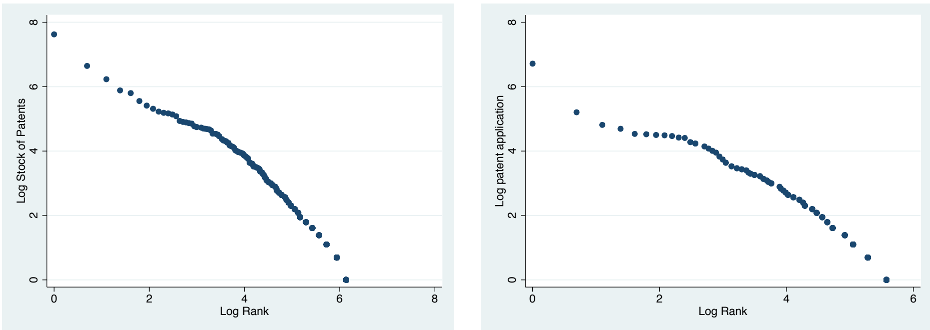
Table 3: Sectoral measure of patent activity

	Patent dummy at t	Patent dummy $[t+1, t+4]$	number patent app.	stock of patent
15 Food and beverages	0.0187	0.0424	87	0.21
16 Tobacco	0.0526	0.2105	2	0.00
17 Textile	0.0168	0.0643	17	0.03
18 Apparel	0.0074	0.0198	11	0.13
19 Leather	0.0289	0.0578	29	0.25
20 Timber	0.0106	0.0798	3	0.08
21 Paper	0.0341	0.0922	17	0.18
22 Printing and publ.	0.0000	0.0000	0	0.02
23 Petroleum and coke	0.0000	0.0000	0	0.05
24 Chemicals	0.1431	0.2524	541	3.75
25 Plastic	0.0584	0.1770	226	0.88
26 Minerals	0.0253	0.0625	29	0.17
27 Metals	0.0470	0.0850	31	0.51
28 Metal products	0.0495	0.1013	76	0.26
29 Machinery	0.1875	0.3347	1095	3.12
30 Computer	0.2059	0.1765	829	93.39
31 Electrical equipment	0.1906	0.3343	225	1.77
32 Telec. equipment	0.1156	0.1850	136	2.47
33 Medical and optical instr.	0.2115	0.3269	76	2.03
34 Cars and trucks	0.1640	0.2540	318	5.03
35 Other automotive	0.1027	0.1964	144	1.30
36 Furniture	0.0288	0.0653	23	0.32
Total	0.0736	0.1417	3915	1.41

Source: INVIND and PATSTAT. In the first column we report the share of firms that apply for a patent in a given year. In the second column we the share of firms that apply for a patent in the following 4 years. The third column reports the total number of applications. The last column reports the stock of depreciated patent.

The distribution of patents activity is uneven also across firms. In figure 3 we depicted in a log-rank plot the distribution of patent application and the stock of depreciated patents. Both distributions are skewed: few firms hold a large share of existing patent stock and apply for a large number of new patents.

Figure 3: Distribution of Stock of Patents, Applications and Citations



Source: PATSTAT. Stock of patents and total number of applications between 2001 and 2005.

4.2 Patent and Export

In Table 4 we get closer to the empirical relationship of interest and see how past exporting and patenting activity affects the probability of future patenting: it emerges a clear and strong monotonicity between past and future patenting propensity; interestingly, even controlling for the past number of patents, export intensity is positively correlated with the probability of future patenting.

Table 4: Relation between stock of patent and export intensity

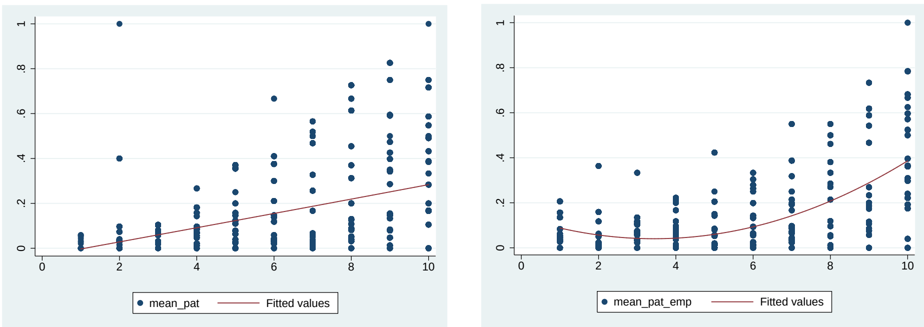
	Export share				
Patent stock	domestic	less 1/3	1/3 to 2/3	more 2/3	Total
Zero	0.007	0.038	0.070	0.054	0.039
1 qrt	0.147	0.220	0.215	0.252	0.221
2 qrt	0.089	0.300	0.393	0.436	0.343
3 qrt	0.455	0.495	0.631	0.653	0.591
4 qrt	0.857	0.868	0.888	0.948	0.908
Total	0.013	0.088	0.198	0.216	0.117

Source: INVIND and PATSTAT. Stock of depreciated patent calculated using perpetual inventory method with an annual depreciation rate of 15%. Categories represents quartile of distributions for firms with stock different from zero

The link between exporting and patenting can be differently appreciated in Figure 4a, where the probability of patenting is plotted by deciles of the level of exports within sector (at any decile, each dot is associated to a specific sector): there is clear linear positive relationship between the level of exports and the probability of patenting. A similar graph where export levels are substituted by employment levels is shown in figure 4b: again it emerges a positive relationship, to say that patenting is more likely among larger firms.

Figure 4: The distribution of the probability of patenting

(a) Export levels | (b) Employment



Source: INVIND and PATSTAT.

In table 5 we explore the relationship between patent and export conditional on firm size. For each sector we divide firms according to their quintiles of employment and export, then for each cell we compute the probability of applying for a patent. Even when we condition on firms size, the probability of patenting increases with export.

Table 5: Probability of Patenting $[t+1, t+4]$

quintiles	Employment					
Export	1	2	3	4	5	Total
1	0.007	0.007	0.011	0.046	0.042	0.015
2	0.052	0.024	0.042	0.044	0.123	0.043
3	0.049	0.057	0.102	0.133	0.150	0.088
4	0.027	0.095	0.097	0.199	0.279	0.167
5	0.103	0.011	0.074	0.091	0.383	0.275
Total	0.035	0.038	0.067	0.126	0.321	0.117

Source: INVIND and PATSTAT. Quintiles are calculated for each sector-year. Each entry represents the share of firms that apply for a patent between $[t+1, t+4]$

The last sets of data we use in the empirical analysis are the Baci-Cepii dataset on world trade flows by sector and country and the Italian trade statistics collected by the Italian statistical agency (Istat). The Baci dataset builds on UN Comtrade but harmonizes the data to reconcile flows reported by importing and exporting countries.[13] Istat's trade data are detailed by sector, 95 provinces and all countries of origin/destination of trade flows.

5 Results

Estimates of equation (4) are displayed in Table 6. The first column shows the results of a very parsimonious OLS specification in which the only controls are the set of year, sector and province dummies. The probability of applying for a patent between t and $t+4$ turns out to be positively correlated with a firm's level of exports at t.

Given the endogeneity issues discussed earlier, in the other columns of the Table we recur to IV estimation using the instrument described in section 3.1. In column (2) IV estimates are derived from the most parsimonious model shown in column (1): according to this estimation, the positive and significant effect of exports on the patent propensity is confirmed; the IV coefficient is larger than the OLS one signalling a downward bias in the OLS estimation due to either a classical measurement error or a reverse causality of the type described in section 3.1. The coefficients of the first stage have the expected signs and the first stage F-statistics, reported in the lower part of the Table, is greater than 10, that is safely above the standard levels of the weak instruments literature (Bound et al., 1995).

To control for the empirical facts that larger firms have a higher propensity to both patenting and exporting and patenting is a very path-dependent activity, in control (3) we add as controls the firm-level lagged $(t-4)$ level of employment and a set of dummies that measure the firm-level existing stock of patents at $t-4$. These dummies have been described in section 3.1. As expected, previous patenting activity is a significant determinant of future patenting, greatly improves the fit of the regression and reduces the size of the IV coefficient of exports that, though, remains statistically significant. This, which is our preferred specification, confirms a sizeable causal impact of the level of exports on patenting propensity: indeed, passing from the 25th to the 75th percentile of the export distribution increases the probability of patenting by 15%, that is half a standard deviation.

We check the robustness of our estimates in three different ways. Firstly, the validity of the exclusion restrictions in our identification strategy crucially depends on the absence of very large Italian exporters that might influence world trade in a certain industry. To preempt this concern, in column (4) we run the same regression as in column (3) excluding those observations where a province has a Balassa index in a given sector larger

[13]For further details see `http://www.cepii.fr/anglaisgraph/bdd/baci.htm`

Table 6: Baseline and robustness

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
log(export)	0.020***	0.032***	0.023**	0.026**	0.019*	0.042**
	[0.001]	[0.010]	[0.011]	[0.012]	[0.010]	[0.021]
employment$_{t-4}$			0.032	0.009	0.027	-0.037
			[0.062]	[0.067]	[0.056]	[0.109]
dstock4y2			0.192***	0.169***		0.204***
			[0.031]	[0.031]		[0.032]
dstock4y3			0.341***	0.334***		0.339***
			[0.033]	[0.034]		[0.032]
dstock4y4			0.620***	0.614***		0.603***
			[0.038]	[0.044]		[0.040]
R^2	0.042					
F		20.82	13.72	11.08	10.94	16.74
$D^2_{\ln \hat{X}^t_{ps}}$		0.759***	0.611***	0.541**	0.584***	0.306***
		[0.178]	[0.165]	[0.172]	[0.178]	[0.097]
$D^3_{\ln \hat{X}^t_{ps}}$		1.136***	0.941***	0.835***	0.905***	0.598***
		[0.199]	[0.179]	[0.187]	[0.198]	[0.102]
$D^4_{\ln \hat{X}^t_{ps}}$		1.687***	1.152***	1.143***	1.112***	0.688***
		[0.215]	[0.193]	[0.209]	[0.211]	[0.113]
Obs	10235	10171	10171	8908	8506	8587

Notes: Robust standard errors in brackets. Each regression includes year, province and 2-digit sector fix effects. Significance: * 10%, ** 5%, *** 1%. Specifications: (1) baseline OLS; (2) baseline IV; (3) = (2) + controls for lagged employment and stock of patent; (4) = (3) if Balassa ≤ 10; (5) = (3) if stock of patent = 0; (6) = (3) if log(export) > 0.

than 10.[14] Results holds by and large unchanged.

In column (5) we address a different issue. In theory, we would like to identify the effect of an increase in the intensive margin of exports (a direct measure of the size of the foreign market) on the extensive margin of patenting. To maximize the number of observations, we have so far estimated equation (4) on all firms and controlled for the past stock of patents so as to capture a kind of extensive margin. To this aim, a neater specification would impose to restrict the sample to firms with zero patents before $t-4$ so that the identification of the causal impact of exports relies only on truly new patenters. The results in column (5), where we base our estimation on this restricted sample, confirms a positive and significant effect of

[14]The Balassa index is computed by dividing the share of world trade of a province in a certain sector by the share of the same province in all the sectors.

the level on exports on patenting propensity among firms with no previous patenting experience; the estimated coefficient is reasonably smaller since the propensity to patent among these firms is lower, and in our data very low, due to the presence of a very high fixed costs.

As a final robustness check, we remove observations with zero exports so as to identify more precisely a foreign market size channel. When we do this (column (6)), we find that not only the main result holds, but the magnitude of the estimated effect doubles and the F statistics of the first stage improves significantly.

5.1 Heterogeneity

Our simple theoretical model suggest that the effect of a trade expansion over the probability to file a patent application is higher for the firms that are closer to the export threshold. This implies that marginal firms are not likely to be involved in this process and the positive effect should be driven by larger and more productive firms.

This idea is tested in Table 7. The first two columns present a sample split between smaller (below the median) and larger (above the median) firms according to the number of employees. Results show that the positive effect estimated in Table 6 is entirely driven by larger firms. As similar result is conveyed by the sample split according to the level of labor productivity (third and fourth columns), according to which only more productive firms tend to innovate more when facing a foreign market expansion. This result is consistent with the evidence found by Verhoogen (2008).

Results for the first stage in Table 7 give additional support to the theoretical predictions. The F of the first stage for smaller and less productive firms is quite low. This implies that, when hit by a trade shock, this group is not likely to change its exporting behavior (i.e. they are *never takers*), since they are too far from the exporting threshold. For larger and more productive firms, instead, the first stage is quite satisfactory, thus implying that an increase of international demand is likely to expand the exports for a sizable number of firms (the so-called *compliers*) due to their proximity to the exporting threshold.

6 Concluding remarks

In this paper we analyzed the effect of an increase of foreign trade on the propensity to innovate at the firm level.

We first presented a simple theoretical model with heterogeneous firms in which we showed how an increase in foreign demand boosts firms incentives to innovate and introduce new products. As the model shows, this effect is asymmetric as it is mainly driven by more productive firms and by companies that have already innovated in the past. Empirical evidence supports the

Table 7: Heterogeneity

	On firm size (employment)		On value added per worker	
	below the median	above the median	below the median	above the median
log(export)	0.0170	0.0200**	0.0110	0.0219**
	[0.0354]	[0.0090]	[0.0143]	[0.0099]
R^2	-0.025	-0.008	0.005	-0.008
F fist stage	0.86	14.89	3.57	17.31
Obs	4236	4272	3916	3912

Notes: IV estimates. Robust standard errors in brackets. Each regression includes year, province and 2-digit sector fix effects. Significance: * 10%, ** 5%, *** 1%.

theoretical predictions. By using an IV approach that exploits sectoral world demand as an exogenous variation for firm-level exports, we find that a rise in foreign sales by a standard deviation increases the probability of a patent application being presented by half a standard deviation (15%). This result is stronger for larger and more productive firms and it is robust to factors like past innovative activities and previous export status.

These results are compatible with the complementarity hypothesis between market size and innovation, as expected future profits due to an expansion of foreign demand are an important driving force that encourages firms to bear the fixed costs of innovation.

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