# Fixed Export Costs and Export Behavior*

Luis Castro† Ben G. Li‡ Keith E. Maskus§ Yiqing Xie¶

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**Abstract**

This paper provides a direct assessment of how fixed export costs and productivity jointly determine firm-level export behavior. Using Chilean data, we construct indices of fixed export costs for each industry-region-year triplet and match them to domestic firms. Our empirical results show that firms facing higher estimated fixed export costs are less likely to export, while those with higher productivity export more. These outcomes are the foundation of the widely-used sorting mechanism in trade models with firm heterogeneity. We also find that the substitution between fixed export costs and productivity in determining export decisions is weaker for firms with higher productivity. Finally, among firms that export, both larger fixed export costs and greater within-triplet productivity dispersion are associated with a greater export volume of the average exporter.

**JEL codes:** F10, F12, F14.

**Keywords:** Sorting, firm heterogeneity, fixed export costs.

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†Faculty of Business and Law, Universidad Privada Boliviana, La Paz, Bolivia.

‡Department of Economics, Boston College.

§Department of Economics, University of Colorado at Boulder. Phone: 303-492-7588. Email: keith.maskus@colorado.edu.

¶Department and Institute of World Economy, School of Economics, Fudan University, Shanghai, China.

# 1 Introduction

The central idea in how firms make export decisions is that they are sorted based on productivity and fixed export costs (Melitz, 2003). Because exporting requires the payment of a fixed cost, only firms that expect sufficiently high profits from exporting choose to pay it (Helpman, Melitz and Yeaple, 2004; Yeaple, 2005). The sorting mechanism has two simple empirical implications. First, for a given level of fixed export costs (FECs), firms with high productivity export. Second, for a given productivity, firms with low FECs export. A direct empirical assessment of these ideas remains absent in the literature, despite extensive evidence that exporters display higher productivity than nonexporters (for instance, Bernard and Jensen, 1999, 2004; Lileeva and Trefler, 2010).

That exporters have a productivity premium is, in itself, insufficient evidence of the sorting mechanism, unless FECs are homogeneous across firms. FECs might be less variable than productivity, though there is no reason to expect them to be identical. Rather, FECs likely vary by industrial and regional characteristics, which is our point of departure. Without accounting for these differences in costs, the exporter productivity premium could be explained by a number of possibilities. For example, firms with high productivity (i.e., low variable production costs) can perform better at designing, marketing, and distributing new goods across borders or are more likely to be chosen as suppliers of global enterprises. In other words, high productivity may not be the key difference between exporters and nonexporters, but rather one manifestation of some systematic differences between them.

A further observation is that empirical studies using micro data find that some nonexporting firms are more productive than some exporting firms, which is inconsistent with the sorting mechanism. This puzzle has been identified among firms in the United States (Bernard, Eaton, Jensen and Kortum, 2003), Belgium (Mayer and Ottaviano, 2008), and Japan (Wakasugi, 2009). We also observe this feature in the Chilean data.

Our aim in this paper is to assess directly the two implications mentioned above by incorporating measures of FECs faced by firms. We use export expenses reported by firms to the Annual National Industrial Survey of Chile to construct indices of FECs for each industry-region-year triplet in Chile. Then we empirically examine how firms' export decisions vary with both productivity and the measured FECs of the triplets in which they reside. Because our measures are built at the triplet level and the estimation is reduced form, our work is not a full test of heterogeneity-based sorting. However, it offers a novel means of estimating FECs and our results support the sorting mechanism.

Our empirical study reaches three findings. The primary finding is that, with productivity held constant, high FECs are associated with low export propensities. Moving from the 25th to the 75th percentile of the FEC indices, export propensity falls by approximately five percent. In Figure 1 we illustrate this fact and our proposed resolution. In the wood industry, one of the largest industries in Chile, the mean of exporters' productivity is larger than that of nonexporters, but there is an overlap between the two distributions. We define high (low) productivity firms as those which are more (less) productive than the 75th-percentile exporter and then compare the FECs between high-productivity nonexporters and low-productivity exporters. Our empirical results show that high-productivity nonexporters face higher FECs than low-productivity exporters.

Two other findings follow from the primary one. One is that for a given export propensity, high productivity and low FECs are substitutable. As FECs fall, we expect lower-productivity firms to enter exporting. This substitution effect decreases as firm-level productivity increases because covering FECs is a relatively smaller concern for high-productivity firms. The other interesting outcome is that at the industry-region-year triplet level, the exported value of an average exporter is greater where either FEC or productivity dispersion is larger. The intuition is that, for a given dispersion of firm productivity, higher FECs raise the productivity threshold for exporting, while for given FECs, a larger dispersion of productivity means that better firms move beyond the productivity threshold. In either case, firms that end up exporting are more productive and thus display larger export volumes, including the average one. In our data, moving from the 25th to the 75th percentile of the FEC indices is associated with an increase in the average exporter's export volume of one half in magnitude.

This paper offers the first direct assessment of the firm-level export sorting mechanism jointly involving productivity and FECs. This analysis is important because whether sorting occurs determines the extent to which firm heterogeneity generates additional gains from trade. Recent models suggest that firm heterogeneity itself does not provide significant additional gains from trade. What may generate large gains is the redistribution effect of firm heterogeneity when firms sort themselves into exporters and nonexporters by productivity.[1] Specifically, social welfare improves when market shares are reallocated from relatively unproductive firms to relatively productive ones. The fact that exporters are more productive than nonexporters is insufficient evidence of this reallocation, because exporters may have other advantages and these advantages may give them large market shares. Thus, market shares are not necessarily redistributed to them from nonexporters.

An additional novelty of our approach is to focus on the estimated fixed costs of engaging in exports, rather than penetrating specific foreign markets. In principle there are two types of fixed costs in international trade: those arising from domestic regional and industrial characteristics and those associated with individual overseas markets (known as marketing costs). Firms pay the former, which we call FECs, to get sorted into exporters, and pay the latter selectively to enter into different markets. The literature has looked primarily into marketing costs (e.g., Arkolakis, 2010; Eaton, Kortum, and Kramarz, 2011; Irarrazabal, Moxnes, and Opromolla, 2010), but has paid less attention to FECs. Available studies infer the existence of FECs from choices about export behavior (Das, Roberts, and Tybout; 2007; Hanson and Xiang, 2011; Maurseth and Medin,

[1]For the recent debate on this, see Arkolakis, Costinot, and Rodríguez-Clare (2012) and Melitz and Redding (2013).

2012; Roberts and Tybout, 1997a). Helpman, Melitz, and Rubinstein (2008) analyze bilateral aggregate trade statistics, taking FECs as a confounding factor to control for. Since FECs and export behaviors refer to the same variations in the data, these studies cannot separate the impacts of these two factors. Our approach, which is reduced-form and data-driven, is geared to make that separation. Moreover, it offers the first estimates of the importance of "behind the border" fixed export charges, which are more relevant for domestic policymakers interested in raising efficiency.

Given the usual lags in extending new ideas to additional areas it is not surprising that differences in FECs among firms have received limited attention in the literature to date. The theory of firm heterogeneity and trade is relatively recent and was founded on productivity differences alone, as represented in the emphasis on this element in early theoretical and empirical work. More recent empirical studies have moved beyond productivity to understanding the significant differences in trade costs among firms, which may have various impacts on firm-level export behavior (Nguyen and Schaur, 2010; Forslid and Okubo, 2011; Carballo, Graziano, Schaur, and Volpe-Martincus, 2014). Differences in firm-level FECs, a specific type of trade costs, have gone largely unnoticed because data on trade costs rarely report variable and fixed elements separately. This represents yet another cognitive lag, in that corresponding theoretical analyses have found the role of FEC differences in determining aggregate trade patterns and welfare effects to be substantial (Jørgensen and Schröder, 2008; Gao and Tvede, 2013). Our work endeavors to bridge this gap. We note that even though our FEC measure is computed at the triplet level, rather than the firm level, the approach is a significant step closer to characterizing this second crucial dimension of firm heterogeneity.

The rest of the paper is organized as follows. In Section 2 we build a theoretical model to guide our later empirical exploration. In Section 3 we discuss data and the construction of FEC indices. Our empirical findings are presented in Section 4 and we provide conclusions in Section 5.

## 2 Conceptual framework

In this section we set out a simple theoretical model based on Melitz (2003) to guide our later empirical analysis. Consider two countries, Home and Foreign (i.e., rest of the world for Home). Consumers in Foreign have an identical demand function for good $j$ made in Home: $q(j) = \gamma(\tau p(j))^{1-\sigma}$, where $\tau > 1$ is an iceberg variable trade cost parameter,[2] $p(j)$ is the price of good $j$, $\sigma > 1$ is a constant elasticity of substitution among goods, and $\gamma$ is a scalar that measures demand intensity. Goods are symmetric, each made by one local firm in Home (thus, $j$ indexes both the good and the firm). All local firms use labor as the only input and face the same local wage rate (normalized to 1). The unit labor requirement of firm $j$ is $a(j)$.

[2]The assumption of iceberg variable trade cost means that when $\tau > 1$ units of the good are shipped, only one unit will reach the consumer.

It can be easily verified that the value exported by firm $j$ in Home is

$$V(j) = (\tau/\alpha)^{1-\sigma}\gamma A(j), \tag{1}$$

where $\alpha \equiv 1 - 1/\sigma$ and $A(j) \equiv a(j)^{1-\sigma}$. Since $A(j)$ is a decreasing function of $a(j)$, we use it to denote firm $j$'s productivity. The larger is $A(j)$ (namely the smaller is $a(j)$), the more productive firm $j$ is. In order to export, firm $j$ has to pay a fixed cost $f(j) = f + u(j)$, where $f$ is a common fixed cost that applies to all firms while $u(j)$ is a random fixed cost specific to firm $j$. Thus, firm $j$'s profit from exporting is

$$\pi(j) = \chi A(j) - (f + u(j)), \tag{2}$$

where $\chi \equiv (1-\alpha)(\tau/\alpha)^{1-\sigma}\gamma$.

Given $A(j)$ and $f$, firm $j$ draws $u(j)$ to determine whether to export. It exports if $\pi(j) \geq 0$, or $u(j) \leq \chi A(j) - f$. Hereafter, we suppress the index $j$ whenever confusion does not arise. Letting firm-level $u$ follow a standard normal distribution, the export propensity of a firm is[3]

$$\Pr[X = 1|A, f] = \Pr[u \leq \chi A - f] = \Phi[\chi A - f]. \tag{3}$$

where $X$, an indicator variable that equals either 0 or 1, is the export decision (1 denotes exporting) and $\Phi[\cdot]$ is the standard normal cumulative distribution function. Equation (3) translates into a Probit model for empirical testing. One hypothesis follows immediately:

**Hypothesis 1** *(i) At the firm level, export propensity is increasing in productivity $A$ and decreasing in fixed export cost $f$; (ii) the marginal effect of $f$ on export propensity is smaller for firms with high $A$ than for firms with low $A$.*

Part (i) of Hypothesis 1 is straightforward. Part (ii) stems from the curvature of $\Phi[\cdot]$. Note that $\partial \Pr[X = 1|A, f]/\partial f = -\phi[\chi A - f]$, where $\phi[\cdot]$ is the standard normal probability density function. Evaluated at a given $f$, a large $A$ means $\chi A - f > 0$ so that $\phi[\chi A - f]$ is decreasing in $A$. Thus, $\partial \Pr[X = 1|A, f]/\partial f$ becomes less negative as $A$ rises.

We now define a threshold productivity $A^*$ such that $\pi = \chi A^* - f = 0$. $A^*$ is not a firm-level variable. It is an increasing function of $f$ and firms with $A < A^*$ expect negative profits. With $A$ given, a higher $f$ is associated with a larger $A^*$ and thus a firm with export profit $\chi A - f$ is less likely to export. However, if the firm exports its exported value will not be smaller than exporters with the same $A$ but different $f$'s. Put differently, since $f$ is not in equation (1), $A^*$ is not binding given that a firm does export, though it does reduce the propensity for a firm to export. This is the second hypothesis we will test:

**Hypothesis 2** *At the firm level, $f$ does not affect exported value through channels other than export*

[3] We follow the literature in using the standard normal distribution, which facilitates a direct linkage between the theory and econometric estimation (see, for example, Helpman, Melitz, and Rubinstein (2008)).

*propensity.*

Next, we are interested in the export behavior of the average exporter. Exporters differ in productivity. To calculate the productivity of the average exporter, we need a distribution function of firm-level productivity.[4] Following the literature, we adopt the Pareto distribution.[5] Assume the distribution of $A$ is $G(A) = 1 - (A_{\min}/A)^g$, where the constant $A_{\min}$ is the location parameter (minimum of $A$) and $g$ is the shape parameter. The larger is $g$, the smaller is the dispersion of $A$. As in the literature, we assume $A_{\min} < \inf_{A,f} A^*$ so that exporters are more productive than nonexporters, and $g > 2$ to ensure a finite variance of $A$. Among exporters, $A_{min} = A^*$, and the mean of $A$ is $\bar{A} = gA_{\min}/(g-1)$, so that the average exporter exports the value of

$$E_u[\bar{V}|A,f] = (\tau/\alpha)^{1-\sigma}\gamma \times \frac{g}{g-1} E_u[A^*|A,f] = \sigma \times \frac{g}{g-1} \times f. \tag{4}$$

Recall that $\sigma$ is the constant elasticity in every exporter's $V$, so that the unique determinants of the average exporter's exported value are $g$ and $f$. Equation (4) leads to the third hypothesis we will test:

**Hypothesis 3** *The exported value of the average exporter is increasing in both $f$ and the dispersion of productivity.*

The intuition behind Hypothesis 3 is the following. The Pareto distribution is skewed and heavy-tailed at the low end. A truncated Pareto distribution remains a Pareto distribution, with the same $g$ but different $A_{min}$ (corresponding to $A^*$ here). With $g$ held constant, $f$ affects $E_u[\bar{V}|A,f]$ only through truncating the productivity distribution of exporters. The larger is $f$, the higher $A^*$ is and thus the higher the average productivity of firms that survive in the exporting business. In other words, an elevated $f$ causes a more fierce Darwinian selection of exporters, thereby raising the exported value of the average survivor. Alternatively, with $f$ held constant (i.e., $A^*$ held constant), a larger dispersion of productivity (a smaller $g$) increases $E_u[\bar{V}|A,f]$ because the distribution of firm-level productivity is now less concentrated at the low end and thus the average productivity of survivors rises. Consequently, the exported value of the average survivor rises.

With Hypotheses 1–3 shown above, we are now ready to conduct our empirical investigation, where we treat $f$ as a variable at the industry-region-year triplet (*irt*) level. That is, firm $j$ draws $u(j)$ and makes its export decision by calculating whether $\pi(j) = \chi A(j) - f_{j\in irt} - u(j)$ is positive. Before testing hypotheses 1–3, we discuss our data sources and construction of $f_{irt}$ and $A(j)$ in the next section.

[4] Among the three hypotheses, only Hypothesis 3 relies on the Pareto distribution.

[5] The Pareto distribution is widely used in the international trade literature (see Helpman, Melitz, and Yeaple (2004), Chaney (2008), and Arkolakis, Costinot, and Rodriguez-Clare (2012)). In our setting, for simplicity we let $A \equiv a^{1-\sigma}$ rather than $1/a$ follow the Pareto distribution. Removing the $\sigma$ from the Pareto-distributed $a^{1-\sigma}$ would not lead to additional findings, but would involve additional assumptions on the relationship between $\sigma$ and $g$. Therefore, we do not pursue that in this paper.

# 3 Data

## 3.1 Overview

Our primary dataset is the Encuesta Nacional Industrial Anual (ENIA, translated as "Annual National Industrial Survey") of Chile. The ENIA covers all manufacturing plants with ten or more workers. Since nearly ninety percent of the plants are single-plant firms, we refer to the unit as firm hereafter.[6] The version of ENIA that we access covers the years 2001-2007 and reports firm-level statistics such as industry code (ISIC, Rev.3), location (administrative region), total sales, exported value, and employment.[7] Panel (a) of Table 1 reports annual statistics for our sample of domestically owned firms.[8] Our data cover 2,835 firms in an average year, of which 18 percent are exporters. All peso values are measured using 2003 prices. Sales and exported value rise over the seven years. Panel (b) reports firm-level statistics. An average exporting firm pays export expenses equal to approximately eight percent of its exported value. We will describe these export expenses in the next subsection. Panel (c) of Table 1 reports statistics at the industry-region-year triplet level, at which we construct fixed export cost (FEC) indices.

The unique geography of Chile provides us the basis for estimating local FECs. As shown in Figure 2, Chile is a narrow and long country.[9] It is located on the west side of the Andes Mountains and the east rim of the Pacific Ocean. As a result, locally made products tend to be exported from within-region ports rather than transported elsewhere and then exported. We find a high correlation between industry-region level exports in the ENIA and the corresponding customs data, indicating that the majority of locally made exported products are shipped through local customs.[10]

We incorporate, as our productivity measure, the logarithm of total factor productivity (TFP)

[6]The percentage of single-plant firms in all plants varies between 87.5 and 89.8 during the years 2001-2007.

[7]Various versions of this dataset have been used by Levinsohn (1999), Pavcnik (2002), Lopez (2008), Volpe Martincus and Blyde (2013), among others. The ENIA data are available for the years 1995-2012. However, the data for 2008 and later do not report information that can be used to identify firms and thus they cannot be matched to the data we use. The ENIA data for the years 1995-2000 can be matched to our data. We did not include them because Chile underwent negative terms of trade shocks and diminished supply of external finance, and meanwhile adopted a highly contractionary monetary policy in the late 1990s. These factors had substantial influences on the trade dynamics at the firm level.

[8]We drop multinational subsidiaries and licensees from the sample because their export decisions are heavily influenced by their overseas parent firms. The industries included in the analysis are listed at the bottom of Table 1. We excluded the food industry because agricultural production is usually subsidized. Manufacturing production is far less subsidized and export promotion usually takes the form of providing information and lower-cost paperwork. There is a variable related to export subsidies in the data. However, its magnitude is small in total and netting it out of export expenses should not affect our findings. Since we do not know exactly what those subsidies refer to (e.g., for covering export expenses or not), we did not include subsidies for analysis in our main specification.

[9]The map in Figure 2 was made and customized for us by a map publisher (MapXL, Inc., website: www.mapsofworld.com).

[10]Because the ENIA does not report shipment details on firms' exports, we aggregate the data to the industry-region level and compare them to industry-region level customs statistics (Appendix A1 provides details on the customs data). We computed the share of region $r$ in Chile's total exports in industry $i$ with both the ENIA data and the customs data. The correlation between the two shares is 0.79 and there is no statistical difference between their means.

for each firm and year. For this purpose we use the Ackerberg-Caves-Frazer (ACF, 2006) method, which builds on the earlier approaches of Olley-Pakes (1996) and Levinsohn-Petrin (2003).[11] The ACF method addresses the endogeneity problem that arises from the correlation between unobservable productivity shocks and input levels, as well as the potential collinearity problem in the earlier approaches. For our statistical analysis, we standardize the TFP with industry-year means and standard deviations. We use logged standardized TFP consistently in the paper. The standardization ensures the comparability of TFP across industries.[12] We also compile firm-level control variables, including capital-labor ratio (KL), the ratio of value added to sales (VA), and the value of imported inputs. These figures are either computed using the ENIA data or directly extracted from there. We also employ average foreign tariff rates as an industrial characteristic that varies over time.[13]

### 3.2 Measurement of fixed export costs (FECs)

Every year exporters in the ENIA report all expenses resulting from export-related activities. These reported export expenses are a remarkable feature of the data, considering that export costs are rarely included in firm-level datasets. Following are several examples of fixed export costs (FECs) that would be a portion of the expenses listed. First, some costs relate to administrative charges, such as export-license fees, which may need to be renewed periodically. Second, there are fixed components of the total costs arising from export activities performed on a regular basis. Examples include the fixed charges incurred in crating, packing, warehousing, consolidation, storage, loading and shipment. In the latter cases total expenses vary with exported values to a certain extent but are not completely variable costs. For instance, crating and packing for exporting involve renting machines and hiring staff, while customs warehouses have minimum usage charges. Our FEC measures aim to capture all such fixed expenses.[14]

The construction of a FEC index consists of two steps. The first step is to regress exporting firms' export expenses on their exported values and extract the fixed effects associated with each industry, each region, and each year. The export expenses are reported as an aggregate variable in the ENIA dataset, so there is just one figure per firm per year. Its theoretical value corresponding to our model is

$$ExportExpenses = f + u + \varrho(1 - \tau^{1-\sigma})V, \tag{5}$$

for an exporter. We specify total variable export cost as $(1 - \tau^{1-\sigma})V$. We assume this cost is

[11]TFP estimates using these methods are widely reported in the trade literature. See, for example, Amiti and Konings (2007), Goldberg, Khandelwal, Pavcnik, and Topalova (2010), and Greenaway, Guariglia and Kneller (2007). In particular, for uses of the ACF method, see Arnold, Javorcik, Lipscomb and Mattoo (2008), Javorcik and Li (2008), and Petrin and Sivadasan (2011). We use skilled labor, unskilled labor and capital stock as our first stage inputs. Electricity consumption is our choice of intermediate input.

[12]When TFP is not normalized, both its means and standard deviation are incomparable across industries.

[13]Appendix A2 provides details on the tariff data.

[14]Roberts and Tybout (1997b) discuss related costs faced by exporters in Colombia, Mexico, and Morocco, but their study focuses on the start-up costs that are sunk after firms break into overseas markets.

shared by the exporter and the importer, with parameter $0 \leq \varrho \leq 1$ denoting the share paid by the former. This share is unobserved by the researcher. Since we have panel data on exporters, we add a time dimension to the specification. Also, we control for the tariff-related elements in the iceberg variable trade cost. Lastly, as noted earlier, our measures of FECs are at the industry-region-year triplet level. With these three considerations reflected, equation (5) becomes

$$ExportExpenses_{jt} = f_{irt} + u_{jt} + (\zeta_1 + \zeta_{irt} + T_{it})V_{jt}, \tag{6}$$

where $\zeta_1 + \zeta_{irt} + T_{it}$ is the variable cost rate, corresponding to the $\varrho(1 - \tau^{1-\sigma})$ in equation (5). Parameter $\zeta_1$ is the firm-specific variable cost rate (tariff excluded), $\zeta_{irt}$ is triplet-specific variable cost rate (tariff excluded), and $T_{it} \geq 0$ represents the tariff rate faced in major foreign markets by exporters in industry $i$ and year $t$.[15] Only exporters have positive export expenses. We exclude first-time exporters from our sample.

We use a linear regression to absorb the error term $u_{jt}$ and isolate the sources of variations in $f_{irt}$:

$$\begin{aligned} ExportExpenses_{jt} = {} & f_i \mathrm{I}_j^i + f_r \mathrm{I}_j^r + f_t \mathrm{I}_j^t + \zeta_1 V_{jt} + \zeta_{2i} \times V_{jt} \times \mathrm{I}_j^i + \zeta_{2r} \times V_{jt} \times \mathrm{I}_j^r \\ & + \zeta_{2t} \times V_{jt} \times \mathrm{I}_j^t + \zeta_T \times T_{it} \times V_{jt} + \varphi' \mathbf{B}_{jt} + u_{jt}, \end{aligned} \tag{7}$$

where indicator variable $\mathrm{I}_j^i$ refers to firm $j$'s industry and equals 1 if firm $j$ is in industry $i$. Since each firm is associated with one industry, $f_i$ captures an industry-specific component of export expenses that is independent of exported value. Indicator variables $\mathrm{I}_j^r$ and $\mathrm{I}_j^t$ are constructed similarly and their coefficients $f_r$ and $f_t$ capture region-specific and year-specific components, respectively. Thus, the sum of these three coefficients captures $f$ in Section 2. Because there may be variable-cost components associated with industry, region, and year, we also include interactions of $V_{jt}$ with the indicator variables, and add $\zeta_T$ to adjust for the importance of tariff-related variable costs relative to non-tariff-related variable trade costs.

The vector $\mathbf{B}_{jt}$ in equation (7) includes two control variables that are not used under our benchmark specification. To motivate these ideas, note that the quantity of exports may seem more relevant to export expenses than value. Unfortunately, the ENIA does not report exported quantity. We address this possibility in secondary regression by controlling for the capital-labor ratio $KL_{jt}$ and the value-added ratio $VA_{jt}$ of firms. The rationale is the following. If the relevant export measure is quantity, we need to isolate the price variations in exported value. Under reasonable assumptions, these control variables accomplish this task and the remaining variation is in the quantity of exports.[16]

[15] Tariff rates faced by Chilean exporters are overall quite low (Pomfret and Sourdin, 2010).

[16] Let $V_{jt} = p_{jt}q_{jt}$, where $p_{jt}$ and $q_{jt}$ are the price and quantity terms, respectively. Suppose $p_{jt} = p(KL_{jt}, VA_{jt})$, then controlling for $KL_{jt}$ and $VA_{jt}$ holds $p_{jt}$ constant and the effective variation in $V_{jt}$ is $q_{jt}$. The association between export prices and capital intensity is widely documented in the literature (Hummels and Klenow, 2005; Hallak, 2006; Manova and Zhang, 2012; Schott, 2004). The value-added ratio is also related to export prices because it captures skill intensity,

With $(\widehat{f}_i, \widehat{f}_r, \widehat{f}_t)$ estimated by equation (7), we next compile the FEC indices by summing and normalizing them. Since exporters pay the export expenses $f_i + f_r + f_t$ regardless of their export volumes, $\widehat{f}_i + \widehat{f}_r + \widehat{f}_t$ is the counterfactual FEC that nonexporters would necessarily pay if they had exported. Thus, we next assign each triplet ($irt$) an FEC value $\widehat{f}_{irt} = \widehat{f}_i + \widehat{f}_r + \widehat{f}_t$ and transform $\widehat{f}_{irt}$ into an index that ranges between 0 and 1 using $f_{irt} = (\widehat{f}_{irt} - \min\{\widehat{f}_{irt}\})/(\max\{\widehat{f}\} - \min\{\widehat{f}_{irt}\})$.[17] Because two different specifications, the benchmark and the case adjusted for $(KL_{jt}, VA_{jt})$, are used to estimate $(f_i, f_r, f_t)$, we construct two indices accordingly. In the end, any firm, regardless of its export status, can be linked to these two FEC indices. The summary statistics of the FEC indices are provided in Panel (d) of Table 1.

Two questions may arise at this point. First, why not construct FECs using the *ir*, *rt* or *it* fixed effects. Second, given our focus on the triplet level, why not use a three-way fixed effect rather than the sum of three separate fixed effects. As for the first question, the reason is that those margins have too few observations. The median two-way units *ir*, *rt*, and *it* have 10, 11, and 26 exporters, respectively. There are not enough variations in the two-way sample to identify FECs. Then the answer to the second question becomes clear. Given that there are few variations along margins *ir*, *rt*, and *it*, there is still less variation at the *irt* margin, making a three-way fixed effect infeasible. In fact, the median three-way unit *irt* has only two exporters.

We note a few additional features of regression (7). First, the regression has accounted for the fact that firms with higher productivity export more. Recall that exported value $V$ equals $(\tau/\alpha)^{1-\sigma}\gamma A$, so that the variation in $A$ has been absorbed by the variation in $V$ and thus captured by the $\zeta$'s in the regression. Thus, self-selection of high-productivity firms to be exporters does not cause endogeneity in regression (7).

Second, we examined how much variation of the FEC indices can be explained by each of $\widehat{f}_i$, $\widehat{f}_r$, and $\widehat{f}_t$. To do so, we estimated nested models by regressing the FECs on the estimated fixed effects, sequentially adding each of the latter. In the case of the benchmark index, we found that all three sets have statistically significant explanatory powers, with the associated Wald tests showing p-values smaller than 0.01. Quantitatively, $\widehat{f}_t$ has the least explanatory power, with an increment to the R-squared statistic of 0.015. In turn, $\widehat{f}_i$ and $\widehat{f}_r$ contribute two thirds and one third of the variations in $\widehat{f}_{irt}$, with R-squared increments of 0.641 and 0.344, respectively. The results in the case of the KL- and VA-adjusted FEC index are similar, with all coefficients being statistically significant and R-squared increments of 0.015, 0.613, 0.372, respectively. Lastly, an interesting reality check is to compute the average level of FECs implied by estimated $\widehat{\psi} + \widehat{f}_i + \widehat{f}_r + \widehat{f}_t$, where $\widehat{\psi}$ denotes the estimated constant term. The FEC-related export expenses amount to 13.6 million Chilean pesos, or 26,400 dollars in 2006. This FEC accounts for 10.7 percent of total export expenses

marketing, R&D costs, and markups.

[17] The sum of fixed effects $\widehat{f}_{irt}$ has to be normalized into an index because the magnitude of estimated fixed effects varies across the two specifications. Econometrically, fixed effects estimated using the two specifications are asymptotically equivalent, though their estimated values are different. Also notice that $\widehat{f}_{irt}$ should not be standardized (i.e., converted into a standard normal distribution) as in the TFP case, because unlike TFP, $f$ is not a firm-level variable.

for the average firm, suggesting that "behind the border" FECs are significant.[18]

**Econometric checks on the FEC indices** We next conduct two checks on the econometric reliability of our FEC indices. The first check is on how heavily the two FEC indices are influenced by firm-level idiosyncratic costs. Note that firm fixed effects are not allowed in regression (7) because firms have time-invariant industries and regions. To determine if firm-level idiosyncratic costs drive our FEC indices, we examine the correlation between our FEC indices and an experimental index constructed using firm fixed effects.[19] The results are reported in Panel A of Table 2. There is no correlation between our FEC indices and the experimental FEC index.

The second check is to see whether the FEC indices are consistent with other measures of business costs. Specifically, we link our indices to the World Bank Enterprise Survey (WBES) of Chile. The WBES evaluates business environments in developing countries by surveying a representative sample of local firms.[20] To make this comparison, we average firm-level WBES responses to the industry-region level that can be matched to our 2006 FEC indices. We regress the indices on the average responses to each of the relevant survey questions, which are listed in the first column of Panel B in Table 2. Regression coefficients are summarized in the remaining columns. We run each regression separately with no fixed effects, with region fixed effects, and with industry fixed effects. As reported in Panel B of Table 2, FECs are found to be higher where there are more frequent water shortages, weaker transportation services, more licensing and permits requirements, and more restrictive customs and trade regulations.

Although the above exercise provides an informative validity check on our FECs, we should be cautious when interpreting the correlation between our FECs and external data. The idea of using fixed effects in regression (7) to construct FEC measures is to isolate the trade costs that do not vary with exported value. A region believed to have higher trade costs than others does not necessarily have higher FECs because such costs might be mainly driven by higher variable costs. Similarly, an industry perceived to have higher trade costs than others may not have higher FECs either. Indeed, the reason we estimate FECs is that prior knowledge, anecdotal evidence or other external information sources cannot distinguish between fixed and variable components in total export costs. Thus, external data can neither prove nor disprove the validity of our FEC indices.

[18] Das, Roberts, and Tybout (2007) find the FECs in Colombia to range from \$10,200 to \$12,200 (converted to 2006 dollars). The relative magnitudes of the two estimates are consistent with anecdotal evidence related to the exporting business in the two countries.

[19] This empirical exercise has three steps. First, we estimate firm fixed effects in export expenses, using the regression

$$ExportExpenses_{jt} = f_j + \widetilde{\zeta}_1 V_{jt} + \widetilde{\zeta}_T \times T_{it} \times V_{jt} + \widetilde{u}_{jt},$$

where tildes distinguish coefficients from those in regression (7). Second, we extract the firm-level estimates $\{\widehat{f}_j\}$ and average them at the industry-region (*ir*) level, denoted by $\widetilde{f}_{ir}$. Correspondingly, we average the previous FEC indices $f_{irt}$ to the industry-region level. Third, we examine the correlation between the two industry-region level indices.

[20] The WBES undertook surveys in Chile in 2006 and 2010. We use the former because this year is also covered by our ENIA sample.

# 4 Empirical Evidence

**Hypothesis 1** Equation (3) in Section 2 directly translates into a Probit model. We introduce interaction terms between FECs and dummy variables, labeled $TFPQ$, that classify firm $j$'s productivity in year $t$ to be in the second, third, or fourth quartile:

$$\Pr[X_{jt} = 1] = \Phi[\iota_f f_{irt} + \iota_{TFP} TFP_{jt} + \sum_{q=2}^{4} \theta_q TFPQ_{jtq} \times f_{irt} + \varphi' \mathbf{Z}_{jirt}]. \tag{8}$$

As before, $j$, $i$, $r$, $t$ are identifiers for firms, industries, regions, and years, respectively. $TFP$ is the standardized TFP defined in Section 3.1, and $\mathbf{Z}_{jirt}$ is a vector of control variables. Hypothesis 1 is then equivalent to $\widehat{\iota}_f < 0$, $\widehat{\iota}_{TFP} > 0$, $\widehat{\theta}_q > 0$, and that the magnitude of $\widehat{\theta}_q$ increases in the quartile $q$.

Table 3 reports the results for various specifications. Columns (1) and (2) use the benchmark FEC index. Column (1) does not include interaction terms while column (2) does. Note that our control variables include the foreign tariff rates, along with firm-level capital-labor usage, value-added ratios, and imported intermediate goods. Year fixed effects are included in all columns to absorb nationwide macroeconomic shocks. Evidently, Hypothesis 1 cannot be rejected. In column (2), firms with productivity in quartile 1 are the reference group. At higher productivity quartiles (i.e., $q$ becomes larger), the negative effect of FECs, $\widehat{\iota}_f + \theta_q$, diminishes. When the KL- and VA-adjusted FEC index is used in columns (3)-(4), the results are similar.

Panel (a) of Table 4 presents the marginal effects of FECs on export decisions based on the coefficients estimated in columns (1) and (3) of Table 3. Taking the benchmark FEC index as an example, we find that moving from the 25th percentile to the 75th percentile of the index causes the export propensity of firms to decrease by five percent.[21] The change is highly similar when the KL- and VA-adjusted index is used. In comparison with Panel (a), Panel (b) of Table 4 presents the marginal effects of productivity on export decisions. Moving from the 25th percentile to the 75th percentile of TFP causes the export propensity to rise by about 13 percent.[22] That is, other factors held constant, a 50-percentile decrease in FECs leads to nearly forty percent as large an effect as a comparable increase in productivity. This is a quantitatively important effect that has not been noted in the prior literature.

**Hypothesis 2** We now test Hypothesis 2 using the regression

$$V_{jt} = \kappa_f f_{irt} + \kappa_{TFP} TFP_{jt} + \omega \lambda(\xi' \mathbf{M}_{jirt}) + \eta_{jt}, \tag{9}$$

where $V_{jt} \geq 0$ is the exported value of firm $j$ in year $t$, $\lambda(\xi' \mathbf{M}_{jirt})$ is the inverse Mills ratio evaluated at $\xi' \mathbf{M}_{jirt}$. The vector $\mathbf{M}_{jirt}$ represents the variables inside the $\Phi(\cdot)$ of regression (8), and the

[21] It decreases from 0.126 to 0.120 (a five-percent decrease).

[22] It increases from 0.117 to 0.132 (a 13-percent increase).

elements of vector $\xi$ are their coefficients. Regression (9) is jointly estimated with regression (8) using the Heckman correction. That is, the effects of FECs and productivity on exported value through forming a profitability threshold of exporting can be viewed as a control variable omitted in the regression of $V_{jt}$ on $f_{irt}$ and $TFP$. This omitted effect can be restored by controlling for the predicted export propensity using the inverse Mills ratio, which is evaluated at the regressors in equation (8).[23]

The coefficients in regression (9) are reported in Table 5. The coefficients of the FEC indices are not significantly different from zero, while the coefficient of TFP is significantly positive. The coefficient of the inverse Mills ratio $\lambda(\cdot)$ is positive and significant, indicating that regression (9) is not independent of regression (8) and thus the profitability threshold effect needs to be corrected. This result is in line with the prediction of our stylized model: FECs do not affect the trade volume of a firm once it finds it profitable enough to export.

The results in Table 5 have another important implication. Suppose that variable and fixed export costs are positively correlated. Then a higher variable cost might also be correlated with a higher $A^*$ and thus lower export propensity. However, if the results in Table 3 captured the effect of variable export costs, we would see a negative and significant coefficients of $f_{irt}$ in Table 5, because unlike a higher $f$, a higher $\tau$ also negatively influences exported value $V$. In short, finding no correlation between $f$ and exported value is a sufficient, but not necessary, condition for the absence of the correlation between $\tau$ and $f$. Given that we find no such correlation in Table 5, our FEC indices are unlikely to be confounded by the negative effect of variable export costs on export decisions.

**Hypothesis 3** In order to test Hypothesis 3, we need to measure the dispersion of TFP. Note that the exported value of the average exporter in equation (4) involves $g/(g-1)$. We do not need to measure $g$ directly if we can find a suitable measure for the ratio $g/(g-1)$, which is sufficient for the test. The term $g/(g-1)$ is actually part of the mean of the Pareto-distributed $A$: $\bar{A} = gA_{\min}/(g-1)$, where the term $A_{\min}$ is redundant. When $A$ is truncated below at $A^*$, $A_{\min} = A^*$ and depends on $f$, making it impossible to distinguish $g/(g-1)$ from $f$ in equation (4).[24] To address this, we use the coefficient of variation (CV) of TFP at the triplet level to measure $g/(g-1)$. Since the variance of a Pareto distribution is $gA_{\min}^2/[(g-1)^2(g-2)]$, its coefficient of variation (CV) equals $[g(g-2)]^{-1/2}$. This CV metric does not depend on the magnitude of $A_{min}$ ($A^*$ here), and is nearly always less than the mean of the Pareto distribution by one.[25]

Table 6 reports regressions of the exported value of the average exporter on the CV of TFP

[23] Note that nonlinearity is used to identify the effect of selection. See Cameron and Trivedi (2009, p.543) for a discussion on the use of nonlinearity in identification.

[24] $A_{min}$ cannot be estimated consistently unless the extreme value theory is used. Taking the extreme value approach would involve additional assumptions. Therefore, we do not estimate $A_{min}$ but use the CV of TFP to approximate $g/(g-1)$.

[25] This does not hold when $g$ is very close to 2. However, in that case, the variance of $A$ approaches infinity, which is not the case of our data.

and our FEC indices at the triplet level. Year fixed effects are included in all columns to absorb nationwide macroeconomic shocks. Column (1) includes the CV of TFP but not the FEC index. Triplets with larger dispersion of productivity are shown to have larger values exported by their average exporters. Column (2) includes the benchmark FEC index but not the CV of TFP. It is clear that higher FECs are associated with larger values exported by average exporters. Column (3) includes both variables and columns (4)-(5) use the KL- and VA-adjusted FEC index. The previous findings continue to hold.

These coefficients constitute further evidence of "survival of the fittest" in the exporting business. Recall from Table 4 that the benchmark FEC index, when moving from the 25th percentile to the 75th percentile, would lower export propensity by five percent. For firms that do export, however, this rise in FECs translates into a nearly 50-percent increase in the exported value of the average one among them.[26] There is also an interesting linkage between Table 6 and the previous Table 5. Higher FECs affect exported value of average exporters by selecting firms with higher productivity to be exporters and thus the average ones among them export more. However, this mechanism does not affect exported value at the firm level, because the profitability threshold effect has been absorbed by the coefficient of $\lambda(\cdot)$.

**Data limitations and implications** We would like to note three data limitations that may affect the interpretation of the previous results. First, our theoretical model in Section 2 is concerned with single-product firms, whereas the ENIA dataset does not report product-level information. The exported values, export expenses, and the variables we used to estimate TFP were reported as single variables aggregated over all products. Consequently, nonexporters in this study are in effect defined in the strictest way. If product-level export status were available, the export indicator $X = 0$ or 1 should be defined at the firm-product level. Without product-level export status, a multi-product firm is defined to be a nonexporter if none of its products is exported. If multi-product firms are pervasive in the data but products within a firm commonly have different export statuses, the FEC differences we estimate in this study would, in reality, be the upper bound of such variations. The reason is that strictly defined nonexporters are, all else held equal, expected to be firms that suffer the most from FECs.[27]

The above reasoning also applies to the second limitation of our data. In practice, exporters may use trade intermediaries to export instead of exporting directly. The ENIA dataset does not report the use of trade intermediaries. Firms that export through intermediaries are counted as

[26] This calculation is the product of the rise in fixed costs (0.070, see Table 4) and the coefficient of the FEC index (0.071 in column (3).

[27] The production of multiple products is not a problem for TFP estimation. The widely used estimation methods, including ACF, Olley-Pakes (1996), and Levinsohn-Petrin (2003) do not require that firms make only one product. TFP is a measure of firm-level productivity rather than product-level productivity. If a firm makes similar products, its TFP reflects the firm's overall technological efficiency for those products. If a firm makes unrelated products (rare in practice), its TFP reflects some weighted average of its technological efficiency across products. The empirical studies on TFP (including the well-known ones cited in footnote 11) rarely consider multi-product issues.

exporters in the ENIA data. If the use of trade intermediaries is pervasive in Chile and firms that use them do not export directly, the FEC differences here would constitute an upper bound in practice.

Lastly, FECs are not randomized in this study and firms may endogenously choose regions and even industries to lower their FEC-related spending. In this sense, the explanatory power of FECs in predicting nonexporting should not be interpreted as causal. However, if manipulation of FECs were taken into account, the explanatory power of these costs would actually be stronger. This is because only firms in high-FEC triplets have incentives to reduce FEC-related costs for exporting (namely, raising $\Pr(X = 1)$). Econometrically, this tends to bias the coefficient of the FEC index in regression (8) towards zero (i.e., less negative). In the extreme case of this tendency, firms would make investments to perfectly offset FEC variations in their triplets, which would eliminate the effect of these costs completely in the regressions. In other words, the endogeneity in firm-level FEC reduction works against finding the negative association between FECs and export propensity.

## 5 Conclusions

Firm-level export decisions mainly depend on two cost elements: average variable costs of production (i.e., productivity) and the fixed costs of selling products abroad (i.e., fixed export costs, FECs). This is a standard assumption in the trade literature, whereas corresponding empirical evidence remains scarce. Our paper closes this gap by documenting the following findings. Both productivity and FECs affect export propensities of firms, whereas only productivity affects exported value at the firm level. In addition, the average exporter's exported value is larger where either the dispersion of productivity is greater or FECs are higher. These findings as a whole indicate that the productivity premium of exporters stems from a sorting mechanism based on both productivity and FECs.

This analysis offers two empirical avenues for future research. First, the concept of a fixed export cost is widely used in theoretical modeling due to its tractability and importance, but largely unstudied empirically due to difficulties in measurement. The FEC indices developed in this paper can be applied to other datasets in which micro-level export expenses are available. Additional empirical efforts in this direction should help deepen our understanding of FECs and their role in theoretical modeling. Second, this paper contributes to new thinking on policies that could expand exports. The conventional wisdom is that productivity improvement is the key to achieving this outcome. However, it may be easier, in policy terms, to reduce local "behind the border" FECs and, as our results suggest, there would be significant impacts on export propensity and volume.

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# Appendix

## A1. Data from the customs of Chile

Customs data were taken from the Chilean National Customs Service (for more information, see www.aduana.cl). The National Customs Service collects information regarding imports and exports from Chile at 90 points of entry/exit, including ports, airports and controlled border crossings. They provide statistics of exports from Chile to the rest of the world, using the 2002 Harmonized System (HS) Classification at the eight-digit level. Statistics are reported in current US dollars (FOB values). To combine these data with the ENIA data, we matched the HS classifications with the two-digit ISIC (rev.3) codes.

## A2. Data on tariff charges

The tariff data are available from the website of the World Integrated Trade Solution (WITS, wits.worldbank.org/wits/) maintained by the World Bank. The WITS website provides access to the database Trade Analysis and Information System (TRAINS), the data of which are collected by the United Nations Conference on Trade and Development (UNCTAD). Since Chile's exports concentrate on five trade partners (China, the European Union, Japan, South Korea, and United States, denoted by $b$ below), we compute their industry-level annual average tariff rates weighted by trade volume. Specifically, we construct the average tariff rate,

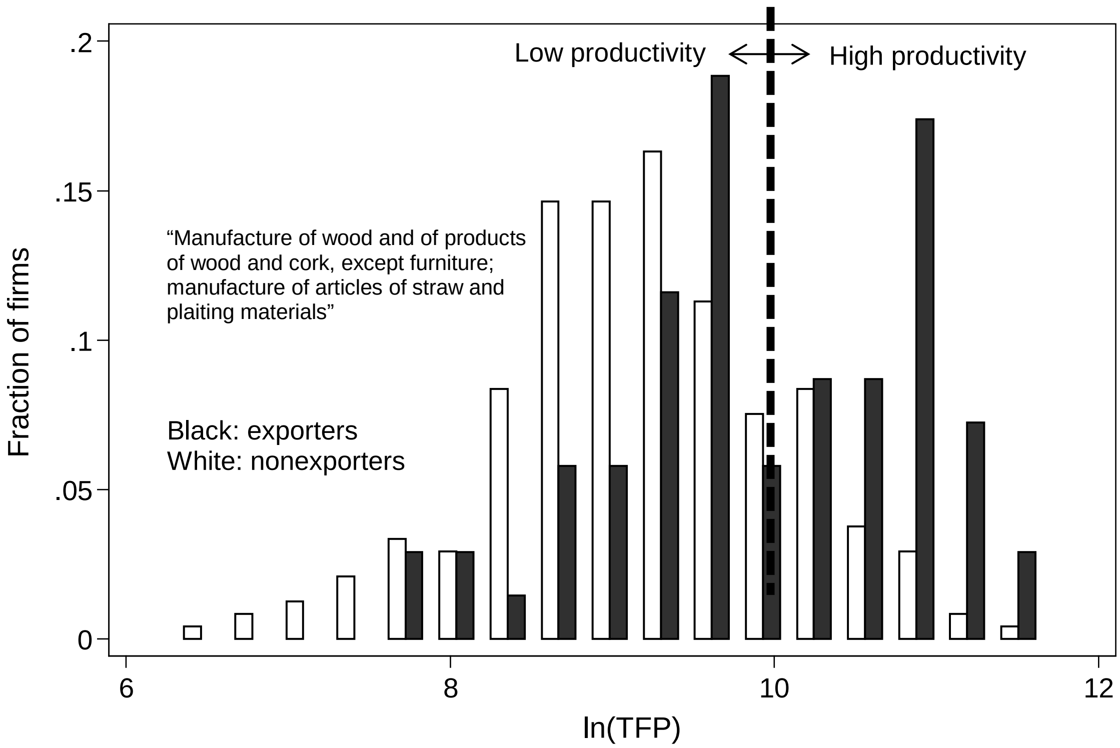
$$T_{it} = \sum_b \varsigma_{bit} \times TARIFF_{bit}$$

where

$$\varsigma_{bit} = \frac{EXPORTS_{bit}}{\sum_b EXPORTS_{bit}},$$

$i$ is the two-digit ISIC (rev.3) code, $t$ is year, $EXPORTS$ is export volume, and $TARIFF_{bit}$ is the average effectively applied rate at the country-industry-year ($bit$) level.

**Figure 1: Productivity overlap between exporters and nonexporters**




Notes: Productivity is estimated using the Ackerberg-Caves-Frazer (2006) method. The vertical dashed line is the 75th-percentile productivity of exporters and we define productivity above (below) this level as high (low) productivity. Using the 60th or 90th percentiles instead does not change our findings.

**Figure 2: The unique geography of Chile**

**Table 1: Descriptive statistics**

| Panel (a): by year* | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Year | No. of firms | No. of exporters | Total sales (tn pesos) | Total export volume (tn pesos) | Average export intensity | Share of exporters |
| 2001 | 2739 | 498 | 9.62 | 3.49 | 0.25 | 0.18 |
| 2002 | 2914 | 443 | 10.06 | 3.09 | 0.27 | 0.17 |
| 2003 | 2906 | 468 | 10.70 | 2.54 | 0.27 | 0.18 |
| 2004 | 3009 | 463 | 14.36 | 4.77 | 0.28 | 0.17 |
| 2005 | 2897 | 425 | 16.53 | 4.44 | 0.28 | 0.17 |
| 2006 | 2787 | 442 | 17.91 | 5.79 | 0.28 | 0.18 |
| 2007 | 2596 | 421 | 19.45 | 5.73 | 0.28 | 0.18 |
| Average | 2835 | 451 | 14.09 | 4.26 | 0.27 | 0.18 |

* Column (3) aggregates the sales of all firms. Column (4) aggregates the export volumes of all exporters. Column (5) is the export volume/total sales ratio averaged across exporters. Column (6) is the ratio of column (2) to column (1).

Panel (b): by firm

| Variable | Obs | Mean | Std. Dev. |
|---|---|---|---|
| Sales (bn pesos) | 19848 | 4.97 | 59.48 |
| Capital (bn pesos)* | 19848 | 2.16 | 22.53 |
| Value added (bn pesos) | 19848 | 3.38 | 51.90 |
| Skilled labor (persons) | 19848 | 37.77 | 115.75 |
| Unskilled labor (persons) | 19848 | 26.36 | 62.36 |
| Export volume (bn pesos) | 3276 | 9.11 | 53.34 |
| Export expenses/export volume | 3276 | 0.08 | 0.50 |

*Capital refers to the sum of values of land, buildings, machines, and vehicles.

**Table 1: Descriptive statistics (cont'd)**

Panel (c): by triplet (industry-region-year)**

| Variable | Obs | Mean | Std. Dev. |
|---|---|---|---|
| No. of firms | 594 | 33.41 | 52.94 |
| No. of exporters | 594 | 5.32 | 9.31 |
| Average-exporter's sales (bn pesos) | 594 | 17.44 | 107.09 |
| Average-exporter's volume (bn pesos) | 594 | 4.27 | 17.05 |

Panel (d): fixed export costs, by triplet

| Fixed export cost index (0 to 1) | Mean | Sd. |
|---|---|---|
| Benchmark | 0.443 | 0.176 |
| Adjusted for KL & VA | 0.436 | 0.179 |

Notes: Peso in the above table means Chilean peso. All peso values are measured using 2003 prices. During the 2001-2007 period, the average exchange rate is 1 US dollar = 606.4 Chilean pesos.

(**) Industries in this study refer to the following two-digit (ISIC, Rev.3) industries: 17 (Manufacture of textiles); 18 (Manufacture of wearing apparel; dressing and dyeing of fur); 19 (Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear); 20 (Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials); 21 (Manufacture of paper and paper products); 22 (Publishing, printing and reproduction of recorded media); 24 (Manufacture of chemicals and chemical products); 25 (Manufacture of rubber and plastics products); 26 (Manufacture of other non-metallic mineral products); 27 (Manufacture of basic metals); 28 (Manufacture of fabricated metal products, except machinery and equipment); 29 (Manufacture of machinery and equipment n.e.c.); 30 (Manufacture of office, accounting and computing machinery); 31 (Manufacture of electrical machinery and apparatus n.e.c.); 32 (Manufacture of radio, television and communication equipment and apparatus); 33 (Manufacture of medical, precision and optical instruments, watches and clocks); 34 (Manufacture of motor vehicles, trailers and semi-trailers); 35 (Manufacture of other transport equipment); and 36 (Manufacture of furniture; manufacturing n.e.c.).

**Table 2: Check on the FEC measures**

*Panel A: variations related to firm fixed effects*

| | Benchmark | | Adjusted for KL & VA | |
|---|---|---|---|---|
| Experimental FEC index based on firm fixed effects | -5.061 | -4.194 | -4.827 | -4.014 |
| | (3.654) | (3.336) | (3.682) | (3.339) |
| Control variables | No | Yes | No | Yes |
| Observations | 99 | 99 | 99 | 99 |
| R-squared | 0.204 | 0.291 | 0.186 | 0.284 |

*Panel B: correlation between FEC indices and WBES surveys*

| | Benchmark | | | Adjusted for KL & VA | | |
|---|---|---|---|---|---|---|
| | No FE | Industry FE | Region FE | No FE | Industry FE | Region FE |
| Average number of incidents of water shortages per month experienced | +** | +* | +* | +* | +* | +* |
| Use own transport to make shipments (yes - 1, otherwise - 0) | +** | +*** | - | +** | +*** | - |
| Customs and trade regulations as the most severe problem (0 - no obstacle to 4 - very severe obstacle) | +*** | +** | + | +*** | +** | + |
| Business licensing and permits as the most severe problem (1 if reported as a firm's top 3 most severe problems, 0 otherwise) | +* | + | +*** | +* | + | +*** |

Notes: Dependent variables are fixed export cost indices in all panels. Panel A: regressions are undertaken at the industry-region level, and control variables are averaged capital-labor ratio, value added ratio, tariff rate, and use of imported inputs. Regressions are weighted by number of exporters. Regressions in Panel B are conducted at the industry-region level. See text for other details of the two panels. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 3: Export decisions, fixed export costs, and productivity**

| Dependent variable: export indicator (0 or 1) | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fixed export cost index | Benchmark | | Adjusted for KL & VA | |
| Fixed export costs | -0.389*** | -0.388*** | -0.413*** | -0.412*** |
| | (0.103) | (0.103) | (0.103) | (0.103) |
| TFP | 0.065*** | 0.029 | 0.065*** | 0.028 |
| | (0.019) | (0.029) | (0.019) | (0.029) |
| Fixed export costs x | | 0.063 | | 0.063 |
| productivity quartile 2 | | (0.040) | | (0.040) |
| Fixed export costs x | | 0.087* | | 0.087* |
| productivity quartile 3 | | (0.048) | | (0.048) |
| Fixed export costs x | | 0.117* | | 0.118* |
| productivity quartile 4 | | (0.066) | | (0.066) |
| Capital-Labor ratio (KL) | 0.338*** | 0.342*** | 0.333*** | 0.337*** |
| | (0.117) | (0.120) | (0.116) | (0.118) |
| Value-added ratio (VA) | 0.325*** | 0.322*** | 0.329*** | 0.325*** |
| | (0.104) | (0.104) | (0.103) | (0.104) |
| Imported inputs | 0.192*** | 0.191*** | 0.192*** | 0.191*** |
| | (0.014) | (0.015) | (0.014) | (0.014) |
| Tariff rate | -0.018*** | -0.018*** | -0.018*** | -0.018*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Observations | 19,845 | 19,845 | 19,845 | 19,845 |

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 4: Marginal effects of fixed export costs and productivity on export propensity**

Panel (a) marginal effects of fixed export costs on export propensity

| Fixed export cost index | Benchmark | | | Adjusted for KL & VA | | |
|---|---|---|---|---|---|---|
| | P(X=1) | dP(X=1)/df | f | P(X=1) | dP(X=1)/df | f |
| 25th percentile | 0.126 | -0.081 | 0.387 | 0.126 | -0.086 | 0.382 |
| Median | 0.123 | -0.079 | 0.428 | 0.122 | -0.084 | 0.429 |
| 75th percentile | 0.120 | -0.078 | 0.457 | 0.120 | -0.083 | 0.455 |
| 75th percentile - 25th percent | -0.006 | 0.003 | 0.070 | -0.006 | 0.003 | 0.073 |

Panel (b) marginal effects of productivity on export propensity

| | P(X=1) | dP(X=1)/dA | A |
|---|---|---|---|
| 25th percentile | 0.117 | 0.013 | -0.538 |
| Median | 0.125 | 0.013 | 0.005 |
| 75th percentile | 0.132 | 0.014 | 0.557 |
| 75th percentile - 25th percentile | 0.015 | 0.001 | 1.095 |

**Table 5: Fixed export costs and exported value**

| Dependent variable is exported value | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Measure of fixed export costs | Benchmark | | Adjusted for KL & VA | |
| Fixed export costs | -0.005 | -0.004 | -0.007 | -0.005 |
| | (0.004) | (0.003) | (0.005) | (0.004) |
| TFP | 0.011*** | 0.007*** | 0.011*** | 0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Capital-Labor ratio (KL) | | 0.103*** | | 0.103*** |
| | | (0.005) | | (0.005) |
| Value-added ratio (VA) | | -0.007*** | | -0.006** |
| | | (0.003) | | (0.003) |
| Imported inputs | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) |
| Tariff rate | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) |
| λ | 0.046*** | 0.025*** | 0.046*** | 0.025** |
| | (0.013) | (0.010) | (0.013) | (0.010) |
| Observations | 19,845 | 19,845 | 19,845 | 19,845 |

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 6: Export volume of an average exporter**

| Dependent variable: export volume of an average exporter | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Fixed export cost index | NA | Benchmark | | Adjusted for KL & VA | |
| TFP coefficient of variation (CV) | 1.542*** | | 1.542*** | | 1.551*** |
| | (0.344) | | (0.345) | | (0.347) |
| Fixed export costs | | 0.076** | 0.071*** | 0.068** | 0.068** |
| | | (0.030) | (0.026) | (0.030) | (0.027) |
| Capital-Labor ratio (KL) | 0.120 | 0.258** | 0.111 | 0.264** | 0.117 |
| | (0.078) | (0.104) | (0.076) | (0.106) | (0.077) |
| Value-added ratio (VA) | 0.249*** | 0.089 | 0.208** | 0.092 | 0.210** |
| | (0.090) | (0.074) | (0.085) | (0.074) | (0.085) |
| Imported inputs | -0.107* | -0.068 | -0.111* | -0.068 | -0.111* |
| | (0.062) | (0.094) | (0.061) | (0.094) | (0.062) |
| Tariff rate | -0.000 | -0.000 | -0.001 | -0.000 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 594 | 593 | 593 | 593 | 593 |
| R-squared | 0.176 | 0.060 | 0.188 | 0.057 | 0.187 |

Notes: Regressions are weighted by the number of exporters in the triplet to address heteroskedasticity. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.