ESSAYS IN APPLIED INTERNATIONAL TRADE

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Abstract

This collection of essays focuses on the utilization of econometric and quantitative methods, together with rich data sets, to study issues in applied international trade. In chapter two I use firm-level data for Mexican exporters to show that theories that emphasize the role of firm heterogeneity can account for cross-sectional facts regarding the distribution of exports across firms and destinations, but that their extension to a dynamic stochastic setting fare less well when contrasted against the data. In addition, I document the internationalization process of new export entrants along both the extensive and intensive margins of trade, which provides a more detailed account of the dynamics of new export entrants than what is currently available in the literature. In chapter three I use transaction data from Mexican exporters to build and estimate a micro founded model of export supply featuring self-discovery. The estimated model accounts well for key features of the observed dynamics of new export entrants, which were documented in chapter two. The model and my estimates imply that the discovery stage in the export market lasts for approximately four years, that the rewards of self-discovery take the form of higher ex-ante probabilities of serving the foreign market and higher export premia, and that temporary shocks to the profitability of serving the foreign market can have long-lived effects on total exports. In chapter four I use data on trade flows together with test scores from the International Adult Literacy Survey, which allows me to construct a novel measure of the distribution of talent in the population, to assess the role that worker heterogeneity has in shaping the pattern of trade. My estimates show that the distribution of skills explains more of the pattern of trade than countries’ endowment of capital and institutional features combined.
Acknowledgments

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For my family, who taught me the value of the gift of education.
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Chapter 1

Introduction

The wider availability of rich data sets concerning a nation’s exports, its determinants, and how these exports are mediated through the decisions of profit-maximizing firms has lead to a surge of research on applied issues in international trade over the last two decades. In this dissertation I use rich data sets, together with modern econometric and quantitative methods to broach issues in international trade that had previously received little to no attention.

In chapter two I use firm-level transaction data for Mexican exporters from the World Bank’s “Exporter Dynamics Database” to provide a comprehensive account of the way that firm-level decisions shape aggregate exports. This chapter contributes to a growing empirical literature that documents how firm-level decisions determine total exports, the distribution of export across destinations and product categories, and the evolution of aggregate exports over time. The results in this chapter confirm that models of export supply featuring heterogeneous firms can account for features of the disaggregated trade data concerning the distribution of a nation’s exports across destinations and across exporting firms. However, it is shown that the implications for the dynamics of firm level trade made by the benchmark extension of the model of Melitz [2003] to a dynamic stochastic setting are at odds with the data. The
three-dimensional nature of the data (two extensive margins and one intensive margin) allow me to document the evolution of the extensive and intensive margins for new export entrants as they survive and grow in the foreign market. I find that firms undergo a process of gradual expansion along all margins. These dynamics for the firm’s process of internationalization are suggestive of a process of self-discovery that firms undergo upon export entry. This idea is explored in a subsequent chapter.

In chapter three I focus on two empirical regularities regarding the dynamics of new exporters: 1. continuation rates that, conditional on survival, are increasing with export tenure, and 2. average growth rates of exports that, conditional on survival, are decreasing with tenure in the export market. These dynamics are at odds with the predictions of standard models of export supply that emphasize the role played by sunk entry costs on firm exporter dynamics. In this chapter I develop and estimate a quantitative model of these new exporter dynamics based on self-discovery: all the dynamics in the model are driven by the learning process that firms undergo in the export market. This force shaping export dynamics will be decreasing in importance with export tenure as firms uncover their true export profitability. The estimated model shows that introducing learning into an otherwise standard model of firm-level export supply goes a long way in explaining the observed dynamics of new exporters. Additionally, the estimated model allows me to quantify the role of learning in shaping the dynamics of export supply and find that: (i) a firm’s discovery stage in the foreign market extends beyond the first year: the value of learning remains positive for the first four years of tenure in the export market; and in the transition to becoming established exporters, surviving firms reap the rewards of self-discovery in the form of large increases to the ex-ante probability of serving the foreign market and to their export premia (the extra payoffs that come from serving the foreign market), and (ii) temporary shocks to the profitability of serving the export market can have long-lived consequences on aggregate trade volumes. In particular, export promotion policies
that temporarily subsidize the fixed costs of maintaining a presence in the foreign market can result in permanent increases in aggregate trade volumes.

Finally, in chapter four I test the empirical relevance of two implications that worker heterogeneity has for comparative advantage and trade patterns: skill abundant countries should export relatively more in skill intensive industries, and skill diverse countries should export relatively more in both low and high-skill intensity sectors of production. One of the most challenging issues for the empirical evaluation of these hypotheses is the limited availability of internationally comparable data on the distribution of skills at the country level. I use test results from the International Adult Literacy Survey (IALS), rather than educational attainment, to provide a novel construction of the distribution of skills at the country level. The IALS data provides a direct measure of the educational capital relevant for workplace productivity held by a country’s working age population. According to my estimates, the distribution of skills explains more of the pattern of trade than countries’ endowment of capital and institutional features combined, at least for the set of exporters under consideration. My results also suggest that estimates found elsewhere in the literature that find support for the hypothesis that capital abundant countries tend to specialize in capital intensive industries are sensitive to controlling for the effect of higher moments of the distribution of talent on the pattern of trade.
Chapter 2

Firms in Mexican Trade

2.1 Introduction

The increasing availability of micro-level data sets that document the activities of individual firms has provided a new window on the determinants of international trade flows. The last two decades have seen a surge of research in international trade, both theoretical and quantitative, that has increasingly drawn attention to the role that firm-level decisions have in understanding the causes and consequences of international trade. Early papers in this literature include, among others, Bernard and Jensen [1995,1999], Melitz [2003], Eaton et al. [2004], and Bernard et al. [2007]. These studies have provided insights into why some producers export and others do not, and the role that trade barriers - such as market entry costs- play in shaping the export market participation of firms.

The literature has stressed the importance of incorporating firm heterogeneity to account for features of disaggregated trade data that cannot be interpreted under the paradigm of a representative firm. Accounting for firm heterogeneity has increased the predictive power of our models for patterns of trade and production and, more

1In this literature, firm heterogeneity is understood as the fact that even within narrowly defined industries some firms are much larger and more profitable than others. The reason behind these differences could be due to, for example, differences in productivity across firms.
importantly, have enhanced our understanding of the margins along which an economy adjusts to trade liberalization that is germane for evaluating the welfare gains from trade (see Melitz and Redding [2015]).

In this chapter I exploit comprehensive firm-level data from Mexico to further our understanding of the relationship between productivity distributions, market size and geography, foreign market presence, and export dynamics for the same set of producers. The three-dimensional nature of this firm-level data, two extensive margins (products and destinations) and one intensive margin, allows me to characterize the dynamics of the extensive margins (products and destinations) and the intensive margins as firms transition from new export entrants into well established exporters. These dynamics further our understanding of the dynamics of growth and survival in export markets and shed light on the process that firms undergo as they evolve from a narrow foreign market presence to the kind of multi-product multi-destination firms that dominate world trade flows (see Bernard et al. [2011]).

The rest of this chapter is organized as follows. Section 2 presents a theoretical (static) framework for multi-product multi-destination firms. Sections 3 contrasts the implications of the model outlined in section 2 to Mexican trade data. Section 4 highlights systematic features of the data related to entry and exit patterns and the participation of firms over time that cannot be addressed with the static framework of section 2. In particular, this section focuses on the dynamics of new export entrants and the way that the foreign market presence of new exporters evolves over time. Section 5 concludes.
2.2 A Framework for Multi-product, Multi-Destination Firms

Variations in trade flows across destinations reflect, among other things, the decisions of multi-product firms to vary the range of their exported products across destinations that have different market conditions. In this section I present a framework to understand how productivity, geography, and market size interact to shape the export market participation decisions of firms. I present a simplified setting that allows me to highlight more easily the main determinants of the export market presence of multi-product firms. In particular, I focus on the firm-level decisions of: (i) whether to serve a particular export market or not, and (ii) conditional on serving the market, which products to export to this market. Thus, I present a partial equilibrium setting. General equilibrium models of multi-product, multi-destination firms that incorporate various of the elements of the framework presented here have been studied by Bernard et al. [2011], Mayer et al. [2014], and Arkolakis and Muendler [2015].

To concentrate attention on the firm-level export decision, I assume that firms are profitable enough to operate domestically and produce goods $g \in \{1, \ldots, G\}$ in the domestic market. To streamline the presentation, I assume that each firm has available a differentiated variety in each of $\{1, \ldots, G\}$ product categories. Furthermore, I assume that the elasticity of substitution across varieties within products is the same as the elasticity of substitution across products. Bernard et al. [2011] assume the more realistic case in which the former elasticity is larger than the latter. The assumption here is closer to the preference specification in Mayer et al. [2014] where the degree of substitutability across the products produced within the firm is the same as the degree of substitutability of products across firms. The product range $\{1, \ldots, G\}$ is the set of products that the firm has available for exporting.²

²Bernard et al. [2011] and Arkolakis and Muendler [2015] allow for the possibility that the range of goods sold domestically may differ from the range of goods sold abroad.
Firms will decide whether they want to enter an export market or not, and conditional on exporting which products to export to each destination. Products are imperfect substitutes in demand and I assume an underlying CES structure such that revenues for a firm selling product $g \in \{1, \ldots, G\}$ to country $j \in \{1, \ldots, J\}$ are given by

$$r_{jg}(q) = \zeta_{jg}D_j q^{\frac{\sigma-1}{\sigma}},$$

where $q$ is the quantity sold by the firm, $\zeta_{jg}$ is the strength of demand for product $g$ in country $j$, $D_j$ is the strength of demand in country $j$ (in general equilibrium this term is related to CES ideal price indices and income), and $\sigma > 1$ is the elasticity of substitution.

The presence of transport costs between the firm’s home country and export destination $j$ imply that a firm producing one unit of output (for any good) will only get to sell $1/\tau_j$ of these units in market $j$ ($\tau_j > 1$ for all $j$). I assume that firms satisfy the demand for their products in the markets they choose to enter (i.e. $q_{jg} = y_{jg}/\tau_j$). Therefore, the export revenue for a firm producing $y_{jg}$ units of good $g$ to be sold in market $j$ is

$$r_{jg}(y_{jg}) = \zeta_{jg}D_j^{\frac{1-\sigma}{\sigma}} y_{jg}^{\frac{\sigma-1}{\sigma}}.$$

On the production side, I assume that the firm is characterized by a productivity profile

$$\left\{ \varphi_g : \varphi_g = \frac{\varphi}{g^\alpha}, \quad g \in \{1, \ldots, G\} \right\},$$

for a firm with “core productivity” $\varphi > 0$. This defines a firm-level “productivity ladder” with decreasing productivity as the firm gets further away from its core product $g = 1$ (see Mayer et. al [2014] and Arkolakis and Muendler [2015]). This productivity profile implies that marginal costs of production are constant for each variety, but are larger for products further away from the firm’s competency. The
cost function for a firm producing product $g$ for market $j$ is given by

$$C_{jg}(y) = f_j + \frac{y}{\varphi_g},$$

where $f_j$ is a per-product fixed cost. In addition, firms face a fixed cost $F_j$ to breach destination $j$. Bernard et al. [2011] interpret $F_j$ as the cost of serving export market $j$ associated with, among other things, the costs of developing a distribution network. On the other hand, $f_j$ can be interpreted as the costs of market research, advertising, and conforming to regulatory standards, among other things. I assume that $(F_j, f_j)$ are paid in the home market in units of output.\(^3\)

The assumption of constant marginal costs in the production of any product for any market together with the assumption of market-specific fixed costs implies that the firm’s profit maximization problem is separable across markets and products. Let $X_{jg}$ be an indicator function denoting the firm’s export status for product $g$ in market $j$. Conditional on $X_{jg}$ the firm chooses its scale of operation $y_{jg}$ to maximize variable profits:

$$\max_y \left\{ \zeta_{jg} D_j \frac{1-\sigma}{\sigma} y^{\sigma-1} - \frac{g^{\alpha}}{\varphi} y \right\}.$$  

\(^3\)For simplicity I assume that the per-product fixed cost is paid in units of the good being produced, while the fixed cost to breach destination $j$ is paid in units of the “core product” or first product introduced into that market. The results established under this assumption are qualitatively no different than if I had assumed that the fixed costs are paid domestically in units of labor, specially given the partial equilibrium framework considered here where the wage that firms take as given would just be another parameter. To see this, assume that producing $y$ units of product $g$ for market $j$ requires hiring labor according to

$$l_{jg} = \alpha_j + \beta_g y.$$  

Taking the wage $w$ as given, the firm faces the cost function

$$C_{jg}(y) = w\alpha_j + w\beta_g y.$$  

Setting $f_j = w\alpha_j$ and $\varphi_g^{-1} = w\beta_g$ would result in the cost function in the main text.
It will prove convenient to define the “destination specific productivity” \( \varphi_{jg} \equiv \varphi_g \zeta_{jg}^{\frac{\sigma}{\sigma-1}} \). Then, the profit maximizing scale of operation for good \( g \) in destination \( j \) is given by

\[
y^*_j = \left( \left( \frac{\sigma - 1}{\sigma} \right) \zeta_{jg}^{\frac{1}{\sigma-1}} \varphi_{jg} D_j \tau_j^{\frac{1}{\sigma-1}} \right)^{\sigma}.
\]

Conditional on export status, a firm with core productivity \( \varphi \) will earn profits in market \( j \) equal to

\[
\tilde{\pi}_j \left( \{X_{jg}\}_{g=1}^G \right) = \sum_{g=1}^G X_{jg} \left[ \psi \varphi_{jg}^{\sigma-1} D_j \tau_j^{1-\sigma} - f_j \right] = F_j,
\]

where \( \psi = \sigma^{-1} ((\sigma - 1) / \sigma)^{\sigma-1} \).

Observe that the destination specific productivity profile \( \{\varphi_{jg}\} \) is positively correlated to the “core” productivity ladder \( \{\varphi_g\} \), but that the destination specific profile of preferences \( \{ \zeta_{jg} \} \) can induce a reordering in the product hierarchy. This implies that product hierarchies are positively correlated across markets, but not perfectly so. We can reorder the products according to the destination specific quality ladder: \( \varphi_1 \geq \varphi_2 \geq \ldots \geq \varphi_G \).

Conditional on exporting to \( j \), we will have that \( X_{jg_j} = 1 \) if and only if

\[
\varphi_{jg_j} \geq B_j,
\]

where I define \( B_j \equiv \psi^{\frac{1}{\sigma-1}} D_j^{\frac{\sigma}{\sigma-1}} f_j^{\frac{1}{1-\sigma}} \tau_j \) as the “barriers to exporting” to country \( j \). These barriers to trade are high when transport costs \( \tau_j \) are high, per-product fixed costs \( f_j \) are high, and the strength of demand \( D_j \) is low. Thus, a firm will choose to export good \( g_j \) to destination \( j \) if its productivity in that product is high enough to overcome the barriers to exporting to country \( j \). Since products have been ordered

\[\text{The “destination specific productivity” is a composite of productivity} \ (\varphi_g) \ \text{and the strength of demand for product} \ g \ \text{in market} \ j \ (\zeta_{jg}), \ \text{that under the assumption of CES preferences enter equilibrium revenue isomorphically.}\]
according to a productivity ladder, the optimal scope (range) in destination $j$ for a firm with “core” productivity $\varphi$ is given by

$$G^*_j(\varphi) = \max \{ g \in \{1, \ldots, G\} : \varphi_{jg} \geq B_j \}.$$ 

Since the destination specific productivity profile $\{\varphi_{jg}\}$ is increasing in “core” productivity $\varphi$, the optimal product scope in all destinations is increasing in firm productivity.

Conditional on exporting to destination $j$, firm profits in that destination are given by

$$\pi(G^*_j) = \psi D^\sigma j \tau_j^{1-\sigma} \left( \sum_{g_j=1}^{G^*_j} \varphi_{jg}^{\sigma-1} \right) - G^*_j f_j - F_j$$

I define $\tilde{B}_j \equiv \psi^{1-\sigma} D^\sigma j \tau_j^{1-\sigma} \left( \frac{F_j + G^*_j f_j}{G^*_j} \right)^{\frac{1}{1-\sigma}} \tau_j$, which is similar to the “barriers to exporting” defined above but in place of the per product fixed costs $f_j$ we have the average fixed costs per product $(F_j + G^*_j f_j/G^*_j)$. Notice that in contrast to $B_j$, $\tilde{B}_j$ does not depend only on characteristics of the export market since it depends on the firm’s optimal scope $G^*_j$, which in turn depends on the firm’s core productivity $\varphi$.

I also define the average product efficiency index in destination $j$ under the optimal scope as

$$H(G^*_j) = \left( \frac{1}{G^*_j} \sum_{g_j=1}^{G^*_j} \zeta^{\sigma}_{jg} j^{-\alpha(\sigma-1)} \right)^{\frac{1}{\sigma-1}}.$$ 

The average product efficiency index is decreasing in the firm’s optimal scope since increasing the firm’s scope requires the introduction of products further down in the productivity ladder.

With this notation, the firm’s export participation decision in market $j$ can be written as: export to destination $j$ if and only if

$$\varphi H(G^*_j) \geq \tilde{B}_j.$$
Thus, a firm will choose to serve destination \( j \) if and only if under its optimal product scope (range) in that destination it is productive enough to overcome the barriers to exporting that range to destination \( j \).

The key relationships between productivity, geography and market size, and export market participation are as follows: a firm with “core” productivity \( \varphi \) will

1. Conditional on exporting to destination \( j \), will export product \( g \) if and only if \( \varphi_{jg} \geq B_j \), and earn revenues for that product equal to

\[
r_{jg} (\varphi) = \sigma \psi \left( D_j^\sigma \tau_j^{1-\sigma} \right) \left( \xi_{jg} g^{-\alpha(\gamma-1)} \right) \varphi^{\sigma-1}.
\]

(a) Optimal product range: the optimal product range for the firm in destination \( j \) is

\[
G_j^* (\varphi) = \max \left\{ g \in \{1, \ldots, G\} : \varphi_{jg} \geq B_j \right\}.
\]

2. Export to destination \( j \) if and only if \( \varphi H (G_j^*) \geq \tilde{B}_j \), where \( H (G_j^*) \) is the average product efficiency index, and earn revenues equal to

\[
r_j (\varphi) = G_j^* \left[ \sigma \psi \left( D_j^\sigma \tau_j^{1-\sigma} \right) \right] \left[ H (G_j^*) \right]^{\sigma-1} \varphi^{\sigma-1}.
\]

This simple set of expressions has profound implications for the three-way relationship between export market presence, productivity, and geography and market size. The threshold conditions \( \varphi H (G_j^*) \geq \tilde{B}_j \) and \( \varphi_{jg_j} (\varphi) \geq B_j \) imply that selection operates at two levels: the former condition implies that only a subset of firms are productive enough to export profitably to destination \( j \), while the latter implies that within the firm there is an endogenous selection of its optimal product range in each destination. These expressions have strong implications for the distribution of exports across destinations and across firms:
1. Destinations with higher barriers to exporting will

   (a) Have lower expected number of firms choosing to export (extensive margin of firm entry).
   
   (b) Have a lower share of a firm’s product range for existing exporters (within-firm product extensive margin).
   
   (c) If the higher barriers to exporting are the result of geography and/or market size, then exports of a given product to a given country by a given firm decrease but there is an ambiguous effect on average exports per firm-product-category because of changes in export composition (within-firm selection of optimal product range).

2. Firms with higher “core” productivity $\varphi$ will

   (a) Reach a larger expected number of export destinations.
   
   (b) Export a larger share of their products to a given destination.
   
   (c) Export more of a given product to a given destination, but may or may not have higher average exports per product due to changes in export composition.

The intuition behind the distribution of export participation across destinations and across firms follows readily from the selection effects that operate across and within firms: higher barriers to exporting make it more difficult for any given firm to export and conditional on exporting make it more difficult to export a large share of the firm’s product range. On the other hand, for given barriers to exporting, more productive firms will overcome more easily the barriers to reaching a destination and the barriers to adding additional products in those destinations.
For the results regarding export volumes, notice that at the firm-country-product level exports are given by

\[ r_{jg}(\varphi) = \frac{\sigma \psi}{\hat{B}^\sigma_j} \left( \zeta_{jg} g^{-\alpha(\sigma-1)} \right) \varphi^{\sigma-1}, \]

and that in every destination, average exports per product in a given firm are given by

\[ \frac{r_j(\varphi)}{G^*_j} = \frac{\sigma \psi}{\overline{B}_j} \left[ H \left( G_j^* \right) \right]^{\sigma-1} \varphi^{\sigma-1}, \]

where \( \hat{B}_j = D^{\frac{1}{\sigma-2}} \tau_j \) are the barriers to exporting arising from geography and market size.

From the first expression above, it is easy to see that more productive firms will export more of a given product to a given destination, and that higher barriers \( \hat{B} \) result in lower exports for a given product by a given firm. From the second expression we can see that higher productivity (barriers) have two distinct effects on a firm’s average exports per product: there is the direct effect that comes from higher (lower) exports of a given product and there is the indirect effect that comes from the firm’s endogenous choice of optimal scope that is reflected in the average product efficiency index \( H \left( G_j^* \right) \), which decreases (increases). In principle the effect of higher productivity (barriers) on average export per product by a firm is ambiguous. Bernard et al. [2011] show that in general equilibrium and under a Pareto distribution for firm productivity these two effects exactly offset one another.

In the next section I contrast some of the implications of the predictions of this framework against firm-level data for Mexican exporters.
<table>
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</tbody>
</table>

*Average Value of Exports per Exporter (Millions of US dollars).

Table 2.1: Participation of Mexican Exporters in International Trade

2.3 The Role of Firms in Mexican Trade Flows

The database that I use covers the period 2000-2007, during which 112,826 different firms participated in Mexican exports, exporting 5,534 different HS 6-digit products to 220 destinations. Table 2.1 presents an overview of the participation of Mexican exporters in international trade. The dataset is such that, on average, every year 34,946 Mexican firms are active in the export market, serving 195 destinations, and exporting 4,756 unique products. The source of the data is the “Exporter Dynamics Database” collected by the Trade and Integration Unit of the World Bank Research Department (see the Annex in Cebeci et al. [2012] for details).

2.3.1 Geography, Market Size and the Distribution of Exports Across Markets

The framework presented in section 2.2 made several key predictions for the way that “barriers to exporting” determine the distribution of a nation’s exports across different export markets. These barriers to exporting summarize the way in which geography ($\tau$), market size ($D$), and market entry costs ($F, f$) affect the export market participation decision of firms. In principle, the measures $B_j \equiv \psi^{1-\sigma} D_j^{\frac{\sigma}{1-\sigma}} f_j^{\frac{1}{1-\sigma}} \tau_j$ and $\tilde{B}_j \equiv \psi^{1-\sigma} D_j^{\frac{\sigma}{1-\sigma}} (F_j + f_j)^{\frac{1}{1-\sigma}} \tau_j$ could be used to produce a hierarchy of export destinations.\(^5\) Eaton et al. [2011] show that for French exporters there is such a

\(^5\)Here $\tilde{B}_j$ can be taken as the barrier to introducing the firm’s first product into destination $j$. In contrast to the definition of $B_j$ in section 2.2, here $\tilde{B}_j$ depends only on the destination market’s characteristics.
stable ranking of export destinations, although not all exporters strictly adhere to this export market hierarchy in the sense that some exporters may export to a given destinations without also exporting to all other higher ranked destinations.6

In this section I contrast the implications of the model of section 2.2 for the effects of the barriers to exporting on the cross-country distribution of exports against Mexican firm level data. For brevity, I report results using 2000 data, but note that results for other years are similar. To construct the measure of barriers to exporting

\[ \tilde{B}_j = \psi \tau^{-\sigma} D_j^{\frac{1-\sigma}{\sigma}} \left( \tilde{F}_j \right)^{\frac{1}{1-\sigma}} \tau_j, \]

I proxy for market size \( D \) by using the log of PPP converted GDP at constant prices and I proxy for transport costs \( \tau \) by using the log distance between Mexico and export destination \( j \).7 In the case of the fixed entry costs I follow Melitz et al. [2008] and model these costs as \( \tilde{F}_j = \exp(\omega \phi_j) \) where \( \phi_j \) is a vector of specific trade costs between Mexico and destination \( j \). This vector includes: (1) a dummy variable for whether Mexico and destination \( j \) share a common language; (2) a dummy variable for whether Mexico and destination \( j \) share the same legal origin; (3) a dummy variable indicating if the relative cost (as percent of GDP per capita) of forming a business is above the median in Mexico and the importing country \( j \), and (4) a variable indicating

---

6Firm-level heterogeneity in transport costs could account for the departure from the export market hierarchy. This heterogeneity could be the result of unobserved firm characteristics such as geographic location. For example, for firms located in Mexico the barriers to exporting to the U.S. are lower than the barriers to exporting to Guatemala. However, there are firms that export to Guatemala that do not export to the U.S. This can be easily explained by noticing that a firms geographic position within Mexico determines a firm-level transport cost to each destination and for firms located in Mexico’s south the barriers to exporting to Guatemala may actually be lower than the barriers to exporting to the U.S. Eaton et al. [2011] introduce idiosyncratic noise to the transport cost \( \tau \) to account for these firm-level departures from the export market hierarchy. If we think of \( \tau_j \) as the average transport cost to destination \( j \) and of the firm-level transport cost to be a draw from a distribution with this mean, then firms face a firm-specific barrier to exporting.

7Distance data is from CEPII (see Mayer and Zignago [2006]) and data for PPP converted GDP at constant prices is from the Penn World Tables https://pwt.sas.upenn.edu
the extent to which Mexico and destination \( j \) share a common religion.\(^8\) I choose the weights \( \omega \) to reflect the effect that these variables have on the probability of observing positive trade flows between a pair of countries.\(^9\) I set the elasticity of substitution \( \sigma = 5 \), a standard value in the literature (see Lai and Trefler [2002] and Alessandria et al. [2013]).

As might be expected, the United States has the smallest “barriers to exporting” for Mexico. I create a barriers to exporting index by normalizing against the United States. According to this index the 10 most attractive destinations for Mexican exporters are: the United States, Canada, Guatemala, Brazil, Spain, Venezuela, France, Colombia, and Germany. To present the results from this exercise I exclude the United States and Canada since they hold a special relationship with Mexico, accounting for 90% of Mexican trade.\(^{10}\) The results reported below include 97 export destinations, covering all continents, for which the “barriers to exporting” index could be constructed.

Figure 2.1 presents the relationship between the barriers to exporting and the share of non-NAFTA exports commanded by an export destination. There is a strong negative association between the barriers to exporting and the log share of non-NAFTA exports. This result is related to the standard gravity results in the literature (see Bernard et al. [2007]), except that here I do not separately identify the effects of distance and market size, but rather focus on how these features of an export

---


\(^9\)The weights \( \omega \) are chosen based on the estimates reported in Table II of Melitz et al. [2008] for a Probit regression of the probability of observing exports between a given pair of countries on observable characteristics that include the previously mentioned variables.

\(^{10}\)In particular, the U.S. accounts for 88% of Mexican trade with over 80% of all active exporters active in that market and with over 93% of all HS-6 digit products sold by Mexican exporters sold in this market. Additionally, I exclude the following countries from the sample: (i) Algeria where 98% of Mexican exports consist of chickpeas and beans; (ii) Tanzania where 93% of Mexican exports consisted of sugar; (iii) Mauritania where 100% of Mexican trade in 2000 was accounted for by a single shipment of railway parts, and (iv) Iran where over 90% of Mexican trade is accounted for by the petrochemical and oil producing industry.
destination combine to produce a hierarchy of markets and see how export activity
is distributed across this hierarchy. In what follows, I decompose the non-NAFTA
export share of a destination into the effects that the barriers to exporting have on
different margins of firm participation in foreign markets.

Figures 2.2, 2.3, and 2.4 look at the relationship between the barriers to exporting
and the number of transactions, firms, and product categories recorded in each
market. The pattern in these figures is remarkably similar to that presented in
Figure 2.1: there is a strong negative association between a nation’s barriers to
exporting and the number of firms, products, and recorded transactions for each
market. Table 2.2 provides further evidence about the role that the barriers to
exporting have on the extensive margin of firm participation and the within-firm
extensive margin of export composition. As can be seen in Table 2.2, the average

---

11I define a transaction as a firm-product pair and a product category as a unique HS-6 digit
product code.
number of transactions, firms, and product categories is substantially higher for countries with below median export barriers than for countries with above median export barriers: the average number of firms and average number of product categories in destinations with below median export barriers is roughly 1450% higher than in destinations with above median barriers. These results are consistent with the framework of section 2.2, that predicted that destinations with higher barriers to exporting will have a lower expected number of firms serving the market (selection across firms), and a lower share of a firm’s product range for existing exporters (within-firm product extensive margin).
Figure 2.3: Barriers to Exporting and the Extensive Margin: No. of Firms. Red dots denote observations with barriers to exporting below the median value.

As a further robustness check I look at the effect of the barriers to exporting on average firm entropy in a destination market. Following Baldwin and Gu [2009], firm entropy in destination $j$ is defined as $ent_j = -\sum_{g=1}^{G_j} s_g \ln (s_g)$ where $s_g$ is the share of product $g$ in the firm’s sales in destination $j$. Entropy captures the extent to which a firm’s sales are skewed toward its largest rather than its smallest products.\footnote{Entropy increases when the number of products sold by the firm increases and when, conditional on the number of products sold, the shares become more even. That is, if a firm sells $N$ products with product shares $\{s_i\}_{i=1}^{N}$ then entropy for $\{s_i\}_{i=1}^{N}$ is lower than for $\{\tilde{s}_i\}_{i=1}^{N}$ where $\tilde{s}_i = \alpha s_i + (1 - \alpha) \frac{1}{N}$, $\alpha \in (0,1)$, $i = 1, \ldots, N$.}

According to the framework of section 2.2 destinations with lower barriers to exporting will exhibit higher firm entropy as firms introduce more products and their sales are less concentrated on their largest product. Figure 2.5 shows that, with the exception of three outliers, there is a negative association between the barriers to exporting and average firm entropy consistent with the framework of section 2.2. In
Figure 2.4: Barriers to Exporting and the Extensive Margin: No of Products. Red dots denote observations with barriers to exporting below the median value.
fact, for destinations with below median barriers there is no destination where all of the firms active in that market concentrate their sales in a single product. On the other hand, 25% of the destinations with above median barriers are such that all the firms active in those markets concentrate their sales in a single product.

Finally, I consider the effects of the barriers to exporting on the intensive margin (sales per variety per firm). In this case it the part of the barriers to exporting that arises from differences in geography ($\tau$) and market size ($D$) that matter.\footnote{This is true for infra-marginal firms. Fixed costs matter for the sales of the marginal firm.} The framework of section 2.2. implied that the effect of the barriers to exporting on the intensive margin could be ambiguous because of the firm’s endogenous choice of product range in each destination. Higher barriers reduce the exports of a given product by a given firm, but they also induce firms to reduce their product scope that increases their average product efficiency index at that destination. This implies that firms will export less for a given product and they will also concentrate their
exports in the best performing products. This in turn implies an ambiguous effect on the firm’s average sales per product. Figure 2.6 exhibits a negative relationship between the barriers to exporting and the intensive margin, although the association is not as strong as those presented in Figures 2.2, 2.3, and 2.4.\textsuperscript{14}

Table 2.3 summarizes the relationships presented in Figures 2.1 through 2.6 by presenting the sample correlations between that barriers to exporting index and the different outcomes of export participation. The framework presented in section 2.2 made sharp predictions regarding the effects of the “barriers to exporting” on the extensive margins of export entry (selection \textit{across} firms) and on the extensive margin of optimal product range (selection \textit{within} firms). Figures 2.2, 2.3, and 2.4 confirm these predictions using firm-level data for Mexican exporters for the year 2000. Furthermore, the evidence suggests that the negative relationship between the

\textsuperscript{14}The sales per firm per variety amongst destinations with below median barriers to exporting is twice as high than for destinations with above median barriers to exporting, but the coefficient of variation of sales per firm per variety amongst the former destinations is half that of the latter.
Correlation with Barriers to Exporting

<table>
<thead>
<tr>
<th></th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Share Non-NAFTA Exports)</td>
<td>-0.92</td>
</tr>
<tr>
<td>log(No. Transactions)</td>
<td>-0.89</td>
</tr>
<tr>
<td>log(No. Firms)</td>
<td>-0.90</td>
</tr>
<tr>
<td>log(Product Categories)</td>
<td>-0.89</td>
</tr>
<tr>
<td>log(Sales per Transaction)</td>
<td>-0.74</td>
</tr>
<tr>
<td>Entropy</td>
<td>-0.17*</td>
</tr>
</tbody>
</table>

*Figure 2.5 shows that there are three outliers in terms of average firm entropy. These correspond to Fiji, the Maldives and Papa New Guinea. For Fiji there is a unique supplier diversified in kitchen appliances/parts. In the Maldives there are two firms diversified in clothing accessories and apparel, and in Papa New Guinea there is a single firm with a 50-50 split of sales. Ignoring theses outliers, the sample correlation between barriers to exporting and average firm entropy is -0.63.

Table 2.3: Barriers to Exporting and Foreign Market Presence: Sample Correlations

barriers to exporting and the share of exports commanded by a destination presented in Figure 2.1 is almost entirely driven by the extensive margins of number of firms and number of products, since the negative association between the barriers to exporting and the intensive margin is less significant.

The predictions of the framework presented in section 2.2 concerning the distribution of a nation’s exports across export destinations are confirmed using Mexican firm-level data. My results are consistent with those found by Bernard et al. [2011] using firm-level data for the United States.

Gravity Reconsidered

In this subsection I disentangle the “barriers to exporting” by focusing on the separate effects that market size and geography have on exports and the different margins of export participation. By decomposing aggregate trade flows into different margins of participation I can assess whether the effect of distance and market size on trade flows operate through firm participation, number of exported products, or the average value of a product exported by a firm. That is, as in Bernard et al. [2007], I reconsider the standard “gravity equation” of international trade.
<p>|
|--------------------------------------------------|</p>
<table>
<thead>
<tr>
<th><strong>GDP</strong></th>
<th><strong>Export Value</strong></th>
<th><strong>Firms</strong></th>
<th><strong>Products</strong></th>
<th><strong>Intensive</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.37***</td>
<td>0.78***</td>
<td>0.75***</td>
<td>-0.16***</td>
</tr>
<tr>
<td></td>
<td>(0.02614)</td>
<td>(0.01312)</td>
<td>(0.01484)</td>
<td>(0.02098)</td>
</tr>
<tr>
<td><strong>Distance</strong></td>
<td>-3.14***</td>
<td>-2.3***</td>
<td>-2.37***</td>
<td>1.53***</td>
</tr>
<tr>
<td></td>
<td>(0.09233)</td>
<td>(0.04634)</td>
<td>(0.05242)</td>
<td>(0.07409)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>1321</td>
<td>1321</td>
<td>1321</td>
<td>1321</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.9829</td>
<td>0.9387</td>
<td>0.9351</td>
<td>0.9586</td>
</tr>
</tbody>
</table>

Standard error in parentheses. *** denotes significance at the 0.1% level.

**Table 2.4: Gravity and Aggregate Mexican Exports**

The value of log exports to destination j at time t can be expressed as

\[
\ln X_{jt} = \ln N_{jt} + \ln M_{jt} + \ln \hat{x}_{jt},
\]

where \(X_{jt}\) denotes the total value of exports in year t to destination j, \(N_{jt}\) the number of exporters in year t in destination j, \(M_{jt}\) the total number of products exported in year t to destination j, and \(\hat{x}_{jt}\) is the average value of exports per firm per product in year t to destination j. I consider a parsimonious specification that includes distance and income as the only explanatory variable, but expand the sample size by taking advantage of the time-series dimension of the data:

\[
\ln Z_{jt} = \gamma_t + \delta \ln \tau_j + \lambda \ln Y_{jt} + \varepsilon_{jt},
\]

where \(\gamma_t\) are year fixed effects that control for factors that may affect exports at time t to all destinations, \(\tau_j\) is the bilateral distance between Mexico and destination j, \(Y_{jt}\) is GDP in j at time t, and \(Z_{jt}\) is either the aggregate value of exports, number of exporters, number of products, or average value of exports per product in turn. 15

Table 2.4 reports the results. Since the dependent and explanatory variables are in logarithms, the estimated coefficients correspond to elasticities. The first column confirms the standard gravity result: trade flows are increasing in destination

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15 Notice that this an extremely simplified specification of the “gravity equation” that does not include terms for multilateral resistance or the price index. Additionally, with data for only one exporter I cannot consider a specification with exporter and importer fixed effects.
GDP and decreasing in distance. The next three columns present the results for the extensive and intensive margins. These results show that the number of exporting firms and the number of exported products are positively related to destination GDP and negatively related to distance, consistent with the implications of the framework presented in section 2.2. Furthermore, the results from Table 2.4 confirm those presented in section 2.3.1: the effects of geography and market size on aggregate trade flows are driven by the extensive margins of number of firms and number of products.

These results confirm those found by Bernard et al. [2007], and like these authors I also find that the elasticities on the two extensive margins - number of firms and number of products- are larger in absolute value than for the intensive margin, and that this is particularly true for the elasticity on importer GDP. Table 2.4 also shows that the elasticity of all outcome variables with respect to distance is larger (in absolute) value than the elasticity on income. This suggest that distance (i.e. transport costs) are a particularly important component of the “barriers to exporting” and that reductions in transport costs have important consequences for export market participation.

On the other hand, to interpret the elasticities on the intensive margin recall that here \( \hat{x}_j = X_j/N_jM_j \) where \( N_j \) is the number of firms serving destination \( j \) and \( M_j \) denotes the unique set of product categories exported to \( j \). Since not all firms will be active in all product categories, the number of recorded transactions \( O_j \) is smaller than \( N_jM_j \). Now, observe that

\[
\hat{x}_j = \frac{X_j}{N_jM_j} = \frac{X_j}{O_j} \cdot \left( \frac{O_j}{N_jM_j} \right) = \hat{x}_j \cdot \left( \frac{O_j}{N_jM_j} \right)
\]
In the previous section it was found that $\bar{x}_j$ is negatively associated with the “barriers to exporting”, presumably because the change in the average efficiency index of exporters resulting from a change in the composition of their exports is not large enough to compensate for the adverse effect that higher barriers to exporting have on the exports of a particular good by a particular firm.

Higher barriers to exporting result in both lower $O_j$ and lower $N_j M_j$, but proportionately speaking $N_j M_j$ decreases more than $O_j$, which means that the ratio $O_j/N_j M_j$ increases and could allow for a positive association between the intensive margin $\bar{x}_j$ and the barriers to exporting. This is indeed what happens in the data as shown by Figure 2.7. Figure 2.7a shows that density $O_j/N_j M_j$ increases as the barriers to exporting increase, while Figure 2.7b shows that there is a positive association between average exports per firm per product category and the barriers to exporting. Bernard et al. [2007, 2011], using data for U.S. exporters, also find that the intensive margin of average exports per firm per product are negatively associated with GDP and positively associated with distance.

**Accounting for the Variation of Exports across Export Destinations**

In the last two sections I have argued that the extensive margins of the number of firms and the number of products are important determinants of the cross-sectional distribution of a nation’s exports across its export markets. In this subsection I take a step further to quantify the importance of each margin of adjustment in explaining the cross-sectional variation of a nation’s exports.

Let $X_j$ denote total export value to destination $j$, $N_j$ denote the number of firms serving destination $j$, and let $M_j$ denote the set of goods exported to destination $j$. Notice that the total number of possible transactions with destination $j$ is $N_j M_j$ (i.e. it is the number of recorded transactions when all firms $N_j$ trade all products

\(^{16}\text{A transaction is defined as an export sale by a firm in a given HS 6-digit category.}\)
Figure 2.7: Barriers to Exporting and the Intensive Margin

(a) Density of Trade

(b) Average Exports Per Firm Per Product
Let $O_j$ denote the number of observed transactions with country $j$ (i.e. the actual number of firm-product pairs that record positive trade with destination $j$), and define the “density of trade” $d_j$ as $d_j = O_j/N_j M_j$. The density of trade is meant to capture that typically firms are only active in a subset of the overall number of products traded. Finally, let $\bar{x}_j = X_j/O_j$ denote average value per transaction with destination $j$. Then, total export value can be decomposed as

$$\ln X_j = \ln N_j + \ln M_j + \ln d_j + \ln \bar{x}_j,$$

where the first three terms on the right hand side are the extensive margins of number of firms, number of products, and density of trade, while the last term is the intensive margin of trade.

The above expression for exports provides the basis for a decomposition of Mexican trade across export markets in a given year. Notice that if we were to run the OLS regression

$$\ln X_j = \beta_N \ln N_j + \beta_M \ln M_j + \beta_d \ln d_j + \beta_x \ln \bar{x}_j + \varepsilon_j,$$

we would obtain $(\hat{\beta}_N, \hat{\beta}_M, \hat{\beta}_d, \hat{\beta}_x) = (1, 1, 1, 1)$ with an $R^2$ equal to 1. For any OLS regression the coefficient of determination can be decomposed as

$$R^2 = \sum_h \delta_h r_h,$$

where $\delta_h$ is the standardized (beta) regression coefficient of the $h^{th}$ explanatory variable and $r_h$ is the sample correlation between the dependent variable and the $h^{th}$ explanatory variable. The quantity $\delta_h r_h$ is the contribution of the $h^{th}$ explanatory variable to the explanation of the variance of the dependent variable (see Theil [1971] for details). Based on this decomposition I can account for the share of the overall
Table 2.5: Decomposition of Mexican Exports Across Trading Partners

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Firms</td>
<td>0.532</td>
<td>0.505</td>
<td>0.512</td>
<td>0.557</td>
<td>0.527</td>
<td>0.534</td>
<td>0.552</td>
<td>0.531</td>
</tr>
<tr>
<td>Products</td>
<td>0.545</td>
<td>0.516</td>
<td>0.526</td>
<td>0.561</td>
<td>0.529</td>
<td>0.524</td>
<td>0.537</td>
<td>0.520</td>
</tr>
<tr>
<td>Density</td>
<td>-0.471</td>
<td>-0.445</td>
<td>-0.456</td>
<td>-0.495</td>
<td>-0.445</td>
<td>-0.447</td>
<td>-0.464</td>
<td>-0.449</td>
</tr>
<tr>
<td>Intensive</td>
<td>0.394</td>
<td>0.424</td>
<td>0.418</td>
<td>0.377</td>
<td>0.389</td>
<td>0.389</td>
<td>0.375</td>
<td>0.398</td>
</tr>
<tr>
<td>No. Destinations</td>
<td>193</td>
<td>193</td>
<td>191</td>
<td>186</td>
<td>197</td>
<td>191</td>
<td>203</td>
<td>206</td>
</tr>
</tbody>
</table>

The results for this decomposition for the period 2000-2007 are reported in Table 2.5. These results reveal that most of the variation in Mexican trade across export markets is due to the extensive margins of number of firms that trade and number of products that are traded. In total, the extensive margin accounts for (roughly) 60% of the overall cross-sectional variation in trade in any given year. This figure is lower than the contribution of the extensive margin found by Bernard et al. [2009] for U.S. trade. These authors find that the extensive margin accounts for 72% of the overall variation in U.S. trade.

2.3.2 The Concentration of Trade: The Distribution of Exports across Exporting Firms

Section 2.3.1 focused on the implications of the framework presented in section 2.2 for the distribution of exports across export destinations. In this section I focus on the distribution of exports across exporting firms. In section 2.2 it was made clear that the concentration of exports across exporting firms depends on the distribution of productivity across these firms. In particular, we know that more productive firms
will serve a higher expected number of export destinations, export a higher share of their product range in any given destination, and export larger volumes globally, in any given market they serve, and for any given product in any given market. Given a distribution \( G(\varphi) \) for “core” productivity \( \varphi \), the model makes strong predictions for the probability that a given product will be sold to a given market\(^{17} \) and the share of total exports that are concentrated in firms of differing productivity.

The distribution of firm-level productivity is not only important to enhance the predictive power of the model regarding export participation and export volumes but, more importantly, can be germane to the evaluation of the welfare gains associated with trade liberalization. In a recent paper, Arkolakis et al. [2012] -henceforth ACR- showed that for a wide class of heterogeneous and homogeneous firm models, the welfare gains from trade could be evaluated with two simple statistics available from aggregate data: a country’s domestic trade share and the elasticity of trade with respect to variable trade costs. However, Melitz and Redding [2015] argue that in models of heterogeneous firms the endogenous decision of firms to enter and exit the domestic and export markets can be important to assess the welfare gains from trade.

Melitz and Redding show that the existence of a single constant trade elasticity and its sufficiency property for welfare are highly sensitive to small departures from the restrictions that make their model fall under the purview of the ACR framework. In particular, one of the key restrictions that have to be imposed on the model for it to belong to the ACR class is that firm productivity \( \varphi \) must be drawn from an untruncated Pareto distribution. They show that even small departures from this functional form for the distribution of firm productivity implies a variable trade elasticity that differs across markets and levels of trade costs.\(^{18} \) In this case, the

\(^{17}\)That is, if \( N \) is the set of firms active in the export market and \( P \) is the set of unique product categories exported, then the framework of section 2.2. together with the productivity distribution \( G(\varphi) \) make strong predictions regarding the share of exporting firms that will be active in any of the \( N \times P \) possible firm-product combinations.

\(^{18}\)As Head et al. [2014] point out, a gravity equation with a constant trade elasticity is misspecified under any distribution other than Pareto.
trade share and the (endogenous) trade elasticity are no longer sufficient statistics for welfare: when firm-level productivity is not distributed according to an untruncated Pareto the micro-structure matters for the evaluation of the welfare gains from trade.\footnote{In particular, Melitz and Redding [2015] show that when the distribution of firm productivity is not an untruncated Pareto distribution the welfare gains from trade depend on the differences in the hazard rates of the distribution of log firm sizes between the domestic and export markets and the response of firm entry to changes in trade costs.}

While firm productivity $\varphi$ is unobservable, we can infer something about the distribution $G(\varphi)$ by looking at the distribution of exports and export participation across firms. In contrast to section 2.3.1, all the results reported in this section include the full set of destinations for Mexican exports. Table 2.6 presents the distribution of exporting firms according to the number of products and destinations they serve. Table 2.6a presents the distribution by the share of firms in each category, while Table 2.6b presents the distribution by share of export value. The main message behind Table 2.6 is that exports are highly concentrated and that multi-product, multi-destination firms dominate Mexican trade: 4.3% of exporting firms account for nearly 50% of Mexican exports.\footnote{In fact, the single biggest exporter accounts for 8.8\% of all Mexican trade and the top 10 exporters account for nearly 30\% of Mexican trade.} In particular, it appears that being multi-product rather than multi-destination is what is particularly important: multi-product firms account for 98\% of Mexican exports versus 60\% accounted for by multi-destination exporters.

According to the framework of section 2.2, this pattern of concentration can be explained by an extremely unequal distribution of productivity across firms that leads to an unequal distribution of exports and export participation across firms as higher productivity firms penetrate more markets, do so with more products, and export more of any given product to any given destination. In light of the framework of section 2.2, an important message behind Table 2.6 is that the distribution of firm productivity is highly skewed. In what follows I delve in deeper into the shape of the distribution of export sales and export participation that, under the CES demand
structure assumed in section 2.2, is tightly connected to the distribution of firm productivity $G(\varphi)$.

### The Size Distribution of Exporters

In this section I document the distribution of exports and export participation across firms by looking at the entire distribution of: export sales across firms, number of transactions per firm, number of products exported per firm, and the number of destinations served per firm.\textsuperscript{21} For each measure of export participation (sales, number of transactions, number of products, and number of destinations) I construct the “size” distribution amongst exporters as the log-log graph of the counter-cumulative distribution $\log \Pr (\text{Size} > x)$ vs $\log (x)$, where “size” is one of the four previous measures of export participation. Plotting the counter-cumulative distribution means that the

\textsuperscript{21}A transaction is defined as recording positive exports for a country-product pair at the firm-level.
$y$–axis will be a measure of “size” plotted against the fraction of firms with at least that “size” along the $x$–axis.

Following Gabaix and Ibragimov [2012], I define for each firm $i$ its “adjusted rank” as

$$R_i = \frac{\text{Rank}_i - 0.5}{N - 0.5},$$

where $N$ is the total number of firms, and $\text{Rank}_i$ is the ranking of firm $i$ in a ranking of “size” from largest (rank 1) to smallest (rank $N$) (i.e. firms are ordered as $\text{Size}_{(1)} \geq \text{Size}_{(2)} \geq \ldots \geq \text{Size}_{(N)}$). Notice that $R_i \approx 0$ if $\text{Rank}_i = 1$ (and $N$ is large), and $R_i = 1$ iff $\text{Rank}_i = N$. Thus, $R_i$ roughly corresponds to the fraction of firms of “size” at least as large as firm $i$.

Figures 2.8 through 2.11 show the size distribution for these different measures of firm “size” in export markets by plotting $\log(\text{Size})$ on the $y$–axis and $\log(\text{Adjusted Rank})$ on the $x$–axis. Additionally, Figures 2.12 through 2.15 present the distribution of export sales in four of Mexico’s top export destinations. For brevity, I report results using 2000 data, but note that results for other years are similar. The left-hand panel of each figure presents the “size” distribution for the full sample, while the right-hand panel presents the distribution for the top one percent of firms (top 10 in the case of the distribution in specific export markets).

By plotting the “size” distribution for different measures of size related to firm participation in export markets, and by doing so in individual export destinations, a remarkable similarity emerges: the basic shape is common for size distributions. In particular, at the tail end of the distribution the relationship between $\log(\text{Size})$ and $\log(\text{Rank})$ is almost linear. The fact that the distribution of export sales for the top firms is nearly linear suggests that in the upper tail sales are distributed approximately Pareto.

The literature has made extensive use of the Pareto distribution as the parametric form for the underlying distribution of productivity across firms (see, for example,
Figure 2.8: Exporter Size Distribution: Sales

Figure 2.9: Exporter Size Distribution: No. of Transaction

Figure 2.10: Exporter Size Distribution: No. of Products
Melitz [2003] and Bernard et al. [2011]). The reason for this is three-fold: it provides a reasonable approximation for the right tail of the observed distribution of firm sizes, it is consistent with simple stochastic processes for firm-level growth, entry and exit (see Simon and Bonini [1958] and Luttmer [2007]), and the Pareto distribution conveys some “scale-free” properties that are useful to provide analytical results. Given the CES demand structure assumed in section 2.2 and the assumption of a Pareto productivity distribution with tail exponent $\zeta$, the distribution of sales is also Pareto with tail exponent $\zeta^* = \zeta / (\sigma - 1)$ where $\sigma > 1$ is the elasticity of substitution. Luttmer [2007] proved this result for the case of a closed economy and Impullitti et al. [2013] show that, despite the effects that selection into and out of exporting can have on the sales distribution, this result extends to the case of an open economy for the distribution of export sales.

Following Gabaix and Ibragimov [2012] I run the OLS log-log rank regression

$$\log (R_i) = a - b \log (\text{Size}_i)$$

to obtain an estimate for the tail exponent of the firms size distribution using export sales as the measure of firm size. I run the log-log rank regression including all firms
Figure 2.12: Exporter Size Distribution: U.S.

Figure 2.13: Exporter Size Distribution: Canada

Figure 2.14: Exporter Size Distribution: Guatemala
Table 2.7: Estimation of Tail Exponent for Size Distribution of Exporters

<table>
<thead>
<tr>
<th></th>
<th>$\hat{a}$</th>
<th>$\hat{b}$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Firms (2000)</td>
<td>$-2.613^{***}$</td>
<td>0.379***</td>
<td>0.9281</td>
</tr>
<tr>
<td></td>
<td>(0.0027416)</td>
<td>(0.0005543)</td>
<td></td>
</tr>
<tr>
<td>Top 1000 (2000)</td>
<td>$-1.874^{***}$</td>
<td>1.021***</td>
<td>0.989</td>
</tr>
<tr>
<td></td>
<td>(0.0044111)</td>
<td>(0.005407)</td>
<td></td>
</tr>
<tr>
<td>All Firms (2004)</td>
<td>$-2.487^{***}$</td>
<td>0.311***</td>
<td>0.8598</td>
</tr>
<tr>
<td></td>
<td>(0.0037795)</td>
<td>(0.0006709)</td>
<td></td>
</tr>
<tr>
<td>Top 1000 (2004)</td>
<td>$-1.831^{***}$</td>
<td>1.019***</td>
<td>0.9817</td>
</tr>
<tr>
<td></td>
<td>(0.005579)</td>
<td>(0.004402)</td>
<td></td>
</tr>
<tr>
<td>All Firms (2007)</td>
<td>$-2.479^{***}$</td>
<td>0.291***</td>
<td>0.8439</td>
</tr>
<tr>
<td></td>
<td>(0.003952)</td>
<td>(0.0006709)</td>
<td></td>
</tr>
<tr>
<td>Top 1000 (2007)</td>
<td>$-1.918^{***}$</td>
<td>1.006***</td>
<td>0.9899</td>
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<tr>
<td></td>
<td>(0.004318)</td>
<td>(0.003214)</td>
<td></td>
</tr>
</tbody>
</table>

Standard Errors in Parentheses. ‘***’ denotes significance at the 0.1% level.

Table 2.7: Estimation of Tail Exponent for Size Distribution of Exporters

and including only the top 1000 firms. Table 2.7 presents the results. As can be seen, the parameter estimates are relatively stable over time. The results in Table 2.7 also suggest that the description of the sales distribution as a power law\(^{22}\) is a better description of the data at the tail end of the distribution than for the full sample. It is also interesting to notice that the tail exponent for the distribution at the upper tail is nearly unity, which implies that the distribution of export sales for the top exporters satisfies Zipf’s Law (see Gabaix [2009]).

Despite the approximately linear relationship between log (Size) and log (Rank) at the tail end of the distribution, Figures 2.8 through 2.15 show that once we consider

\(^{22}\)That is, that $\Pr (\text{Size} > x) \approx a x^{-b}$, where $b$ is the power law or tail exponent.
the distribution of sales across all active exporters there is a noticeable curvature in this relationship. This deviation at the lower end of the distribution from the linear relationship predicted by a Pareto distribution implies that firms at the lower end of the distribution are larger than what would be predicted by

$$\log (\text{Size}_i) = \frac{\hat{a}}{b} - \frac{1}{b} \log (R_i),$$

where \((\hat{a}, \hat{b})\) are the estimates from Table 2.7. This result was also found by Eaton et al. [2011] for the distribution of export sales of French firms.²³

The most commonly used alternative to the Pareto distribution is the log-normal distribution that maintains some of the desirable analytic features of the Pareto, can be generated under equally plausible stochastic processes for firm growth (see Eeckhout [2004]), and provides a better fit to the complete distribution of firm sales rather than just approximating the right tail. To see this last point, assume that

$$\varphi = \exp (z) \text{ where } z \sim N(0,1)$$

so that productivity is log-normal. Figure 2.16 presents the relationship between \(\log (\varphi)\) and \(\log (\text{Rank})\) for 100,000 draws from a log-normal distribution. As can be easily seen, the relationship between \(\log (\text{"Size"})\) and \(\log (\text{Rank})\) is approximately linear at the tail end, but showcases the curvature observed in Figures 2.8 through 2.15 for the full sample.

Since assuming log-normal productivity rather than Pareto has consequences beyond the “fit” of the sales distribution, as argued by Melitz and Redding [2015], I now look more closely at the idea that export sales are distributed log-normal rather than Pareto. I test for the normality of \(\log (\text{Size})\) by “standardizing” the variable “size” (i.e. subtract its mean and divide by its standard deviation) and then comparing the empirical distributions of the standardized data to the standard normal distribution.²⁴

²³Ijiri and Simon [1974] find a similar result for the size distribution of the top 831 industrial firms in the Fortune data for 1969.

²⁴To construct the empirical pdf I use a kernel density estimate of the distribution. The estimation of the kernel density is performed using the “Normal Reference Rule” (see Silverman [1986]): assuming that the density to be estimated is smooth, then if a Normal kernel is used, set the
Figure 2.16: The Size Distribution for a Log-normal \((N = 100,000)\)

Figures 2.17 and 2.18 compare the empirical distribution for \(\log(\text{Size})\) against the standard normal distribution and presents the Q-Q plot for \(\log(\text{Size})\), which plots the empirical quantiles against the theoretical quantiles of the normal distribution. Figure 2.17 presents the results based on the full sample, while Figure 2.18 presents the results based on the sample that only includes the top 1% of firms. For brevity, I present the results for the initial, midpoint, and final years of the sample.

Figure 2.17 shows that log-normality provides a “reasonable” approximation to the complete distribution of firm export sales. Performing the same exercise on the subset of the top one percent of firms, Figure 2.18 shows a deviation from log-normality at the tail end of the distribution.

Head et al. [2014] show that assuming log-normality for the distribution of firm-level productivities rather than Pareto can have important consequences for the evaluation of welfare gains from trade. In particular, they show that the share of firms that enter successfully into exporting affects the gains from trade in the log-normal case, but not in the Pareto one. That is, they show that it is not only the behavior bandwidth to \(h_n = 1.06\hat{\sigma}n^{-\frac{1}{5}}\), where

\[
\hat{\sigma} = \min \left\{ \text{standard deviation}, \frac{\text{interquartile range}}{1.34} \right\}.
\]
Figure 2.17: Testing for Log-normality: Full Sample. Going from left to right, the panels depict the distribution for the years 2000, 2004, 2007.

Figure 2.18: Testing for Log-normality: Top 1% of Firms. Going from left to right, the panels depict the distribution for the years 2000, 2004, 2007.
in the right tail of the productivity distribution that matters for welfare. This is consistent with the argument in Melitz and Redding [2015].

The evidence presented in Figures 2.8, 2.17, and 2.18 and Table 2.7 can be interpreted as saying that the distribution of export sales across firms is best described as a distribution that seems to be log-normal over a broad range, but changes to a power-law (Pareto) distribution for the last few percentiles.\(^{25}\) This is consistent with the results of Head et al. [2014] who, using data on French exporting firms, find that the log-normal distribution can explain 99.9\% of the variation in the empirical quantiles of the sales distribution of exporters, compared to 80\% for Pareto. It is only far out in the upper tail of the sales distribution that Pareto provides a better account of the empirical distribution.

**Accounting for the Variation of Exports across Firms**

In this subsection I quantify the contribution of each of the firm’s margins of adjustment in explaining the cross-sectional variation of exports across firms. Total firm exports can be expressed as

\[
\ln X_f = \ln M_f + \ln d_f + \ln \hat{x}_f,
\]

where \(X_f\) are firm \(f\)’s exports, \(M_f\) is the number of products exported by the firm, \(d_f\) is the number of destinations reached by the firm and \(\hat{x}_f\) are average exports per product per destination. As in section 2.3.1, I quantify the contribution of each margin of adjustment according to the decomposition:

\[
\rho_{M,X} \frac{sd(\ln M_f)}{sd(\ln X_f)} + \rho_{d,X} \frac{sd(\ln d_f)}{sd(\ln X_f)} + \rho_{x,X} \frac{sd(\ln \hat{x}_f)}{sd(\ln X_f)} = 1,
\]

\(^{25}\)Bee et al. [2011] provide support to the theory that distributions with log-normal bodies and Pareto tails can be generated as mixtures of log-normally distributed units.
where $\rho_{Z,X}$ is the sample correlation between $\ln(Z)$ and $\ln(X)$.

Table 2.8 reports the results for the period 2000-2007. The results show that it is the intensive margin that explains most of the variation in exports sales across firms, accounting for roughly 68% of the observed variation. This result suggests that it is the fact that more productive firms export more of any given product to any given destination that drives the distribution of export sales across firms, rather than the fact that more productive firms export to more countries and export larger shares of their product range. In terms of the extensive margin, it is the variation in number of products that explains more of the variation in export sales rather than the variation in destinations reached.

### 2.4 Heterogeneous Firms and Export Dynamics

Section 2.3 showed that the framework of section 2.2, that emphasizes the relationship between export participation and the firm-level decisions of firms of disparate productivity levels, is successful in accounting for patterns in the disaggregated trade data concerning the distribution of exports across foreign markets and across exporting firms. In this section I consider this type of industrial structure in a stochastic dynamic environment, where firms face aggregate and idiosyncratic shocks that can
lead to entry into and exit out of exporting, and contrast its main implications against the data.

2.4.1 A Framework for the Dynamics of Export Supply

In a dynamic setting with forward-looking firms, the dynamics of firm-level export supply can be strongly affected by the structure of the market entry costs faced by firms. For example, complementarities in market entry costs as suggested by Morales et al. [2015], where entry costs in a given market depend on how similar it is to other countries to which the firm has previously exported, imply that exporters cannot make independent entry decisions for each destination market. In the presence of such complementarities there is path dependence in a firm’s entry pattern. Additionally, such models are complicated because they imply that firms must examine the dynamic implications of every possible combination of export destinations.

The empirical evidence regarding the importance of these complementarities in market entry costs is mixed. Morales et al. [2015] find evidence in favor of significant complementarities in the up-front costs of exporting using firm-level data from Chilean firms in the chemical industry. On the other hand, McCallum [2014] -using a panel of U.S. manufacturing firms- finds that market entry costs are market specific and that complementarities are of limited importance. I abstract from these forces and consider a single product and single destination version of the framework of section 2.2 so that I may highlight key economic forces shaping the dynamics of firm-level export supply in the simplest way possible.

I present a simplified version of the framework considered by Das et al. [2007] and Ruhl and Willis [2014]. By focusing on a single-product, single destination I reduce the problem to a simple binary exporting decision that emphasizes the entry into and exit from exporting of heterogeneous firms. Recall that in section 2.2, the net profits from exporting for a single-product, single-destination firm with core productivity
where given by $\pi(\varphi) = \psi D^\sigma \tau^{1-\sigma} \varphi^{\sigma-1} - F$. Now, I assume that firms face: (i) Aggregate shocks: $D_t = \exp(\epsilon_t) D$, where $\epsilon_t$ is a shock to “market size” that affects all firms equally, and (ii) Idiosyncratic shocks: $\tau_{it} = \exp(\zeta_{it}) \tau$ and $\varphi_{it} = \exp(\zeta_{it}) \varphi$, where $(\epsilon_{it}, \zeta_{it})$ are idiosyncratic shocks affecting firm profitability (i.e. the firm’s marginal costs).

Finally, market entry costs are given by

$$F_{it} = F + (1 - X_{it-1}) F_s,$$

where $F$ denote per-period fixed costs that have to be paid anytime the firm decides to serve the foreign market, and $F_s$ denote “sunk” entry costs that have to be paid up front every time the firm starts or resumes exporting. In this setting, the decision to export today is not purely determined by the per period profit

$$\pi(\epsilon_t, \zeta_{it}, \varphi_i) = \exp(\sigma \epsilon_t + (\sigma - 1)(\zeta_{it} - \zeta_{it})) \psi D^\sigma \tau^{1-\sigma} \varphi^{\sigma-1} - F_{it},$$

since export status today has implications for the market entry costs paid by the firm tomorrow. It is the presence of these sunk entry costs that makes the firm’s problem truly dynamic. Otherwise the firm would just face a sequence of static profit-maximization choices.

Define $V^1_{it+1}$ as the firm’s continuation value conditional on exporting today and $V^0_{it+1}$ as the firm’s continuation value conditional on not exporting today. Then, the firm will choose to serve the foreign market at $t$ (i.e. $X_{it} = 1$) if and only if

$$\pi(v_{it}; \varphi_i) + (\beta \delta) \mathbb{E}_t [V^1_{it+1} - V^0_{it+1}] - F_{it} \geq 0,$$

where $v_{it} = (\epsilon_t, \zeta_{it}, \varphi_{it})$, $\beta$ is the time-discount factor, $1 - \delta$ is the probability of exogenous firm death, and $\mathbb{E}_t [\cdot]$ denotes expectation conditional on information at $t$.  

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This condition can be re-written as

\[ \tilde{\varphi}_{it} \geq \left[ \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} \tau (F_{it} - O_{it})^{\frac{1}{1-\tau}} \right], \]

where \( \tilde{\varphi}_{it} = \exp(\gamma v_{it}) \varphi_i \) denotes the firm’s “current profitability” and \( O_{it} \) denotes the “option value” of the firm. This option value is part of the return to becoming an exporter today since it summarizes, given the perceived distribution of future potential exporting profits, the value to the firm of being able to continue exporting next period without incurring the start-up costs \( F_s \). The fact that firms can preserve their export status without having to incur the start-up cost once again means that, in the data, we should expect to see entering firms maintain their export status in the immediate periods after export entry.

In the absence of sunk entry costs, \( V^1_{i,t+1} = V^0_{i,t+1} \) and the above condition can be written as

\[ X_{it} = 1 \iff \tilde{\varphi}_{it} \geq B, \]

where \( B = \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} F^{\frac{1}{1-\tau}} \) are the “barriers to exporting” as defined in section 2.2. In this case, the firm comes in and out of exporting as aggregate and idiosyncratic shocks \( v_{it} = (\epsilon_{it}, \varepsilon_{it}, z_{it}) \) move the firm’s current profitability up and down.

The export participation condition

\[ X_{it} = 1 \iff \tilde{\varphi}_{it} \geq \left[ \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} \tau (F_{it} - O_{it})^{\frac{1}{1-\tau}} \right], \]

shows that the presence of sunk entry costs generates selection not only on a firm’s current profitability, but also on its expectations about its future profitability (through the option value). In the absence of sunk entry costs firms will export today if and only if they expect to earn profits in the export market today. On the other hand, forward-looking firms that face sunk entry costs may decide to export today even at
a loss if they expect high export profits in the future. Furthermore, changes in option values that arise from changing expectations about the future distribution of potential export profits can induce large changes in the return to becoming an exporter, even if current profits are unaffected. For example, anticipated reductions in transport costs $\tau$ could lead to more export entry today even with no changes to current export profits.

Das et al. [2007] show that these option values are the largest component of export value for most producers and that they are particularly important in certain industries. Additionally, they show that that for many of the smaller firms in their study, the option value of being able to export in future years without paying entry costs substantially exceeds the export profits that they expect to earn in the current year. Thus, they argue, there is a well-defined sense in which history and expectations are important for many producers.

Impullitti et al. [2013] consider a general equilibrium version of the framework presented here. Their key result establishes that sunk costs of entry, coupled with idiosyncratic shocks to firm profitability, creates a wedge between the efficiency level at which firms decide to start exporting, $\varphi_H$, and the efficiency level at which firms decide to stop exporting, $\varphi_L$ (see also Dixit [1989]). The interval $(\varphi_L, \varphi_H)$ is a “band of inaction” (that is endogenously determined in the model). That is, there is a range of efficiency levels where the optimal decision is to stick with the status quo: non-exporters will not enter the export market and exporters will not leave it. Therefore, in contrast to section 2.2, a firm’s efficiency is not a sufficient statistic to determine the export status of a firm: a firm’s history has to be taken into account. To see this last point, notice that it is possible that

$$\exp(\gamma v_{it}) \varphi_i \geq \left[ \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} \tau (F - O_{it})^{\frac{1}{1-\sigma}} \right]$$

$$\exp(\gamma v_{it}) \varphi_i < \left[ \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} \tau (F + F_e - O_{it})^{\frac{1}{1-\sigma}} \right],$$

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so that two firms with the same core productivity $\varphi_i$ and the same shocks $v_{it}$ (and thus the same expectations about future profitability), may have different export status at $t$ depending on their export status at $t - 1$.

In a stochastic dynamic environment both firm-level dynamics and aggregate entry and exit patterns and export dynamics depend on the nature of the shocks that firms confront. However, one immediate implication of the export participation condition

$$X_{it} = 1 \iff \varphi_{it} \geq \left[ \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} \tau (F_{it} - O_{it})^{\frac{1}{\sigma-1}} \right],$$

is that firms with higher core productivity $\varphi$, that have higher expected “current profitability” and higher option values, should have a more persistent participation in export markets. Since firms with higher core productivity export more, these “continuing” firms should account for the largest share of exports in a given year. Additionally, variations in the export volume of these firms should account for most of the year-to-year variation in total exports.

In any given year, firm’s selecting out of exporting will be such that

$$\exp (\gamma v_{it}) \varphi_i < \left[ \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} \tau (F - O_{it})^{\frac{1}{\sigma-1}} \right],$$

while firms selecting into exporting must be such that

$$\exp (\gamma v_{jt}) \varphi_j \geq \left[ \psi^{\frac{1}{1-\sigma}} D^{\frac{\sigma}{1-\sigma}} \tau (F + F_s - O_{jt})^{\frac{1}{\sigma-1}} \right].$$

This implies that in any given year the firms selecting into exporting are expected to have a higher core productivity than the firms that are selecting out of exporting (the former have to pay the up-front sunk entry cost while the latter do not). As such, entering firms are expected to have higher export volumes than exiting firms. Additionally, the average exports of both entering and exiting firms should be lower.
than the average exports of incumbent firms that are largely driven by the high core productivity “continuing” firms.

Impullitti et al. [2013] show that there is a stationary density for firm efficiency that implies that there is a stationary mass of exporters. This in turn implies that there is a steady state flow of firms entering into and exiting from exporting. At an aggregate level, the extension of the single-product and single-destination framework of section 2.2 to a dynamic stochastic environment makes the following predictions:

1. There is a steady state mass of exporters and a steady state flow of firms entering into and exiting from exporting.

2. “Continuing” firms should account for most of total exports and most of the year-to-year variation in total exports.

3. Entering firms are expected to have larger export volumes than exiting firms.

4. Both entering and exiting firms are expected to have lower export volumes than incumbent firms.

5. Entering firms are expected to maintain their export status in the immediate periods after export entry.

At the firm level the stochastic process for the idiosyncratic and aggregate shocks affecting current profitability and the distribution of future potential export profits has important consequences for the dynamics of the firm-level export supply decision. The performance of an export entrant depends on the particular realization of the sample path of the shocks faced by the firm \( \{v_{it}\}_{t=1}^{\infty} \). The standard assumption in the literature has been to assume that \( (\epsilon_t, z_{it}) \) are stationary and serially correlated (see Das et al. [2007] and Ruhl and Willis [2014]). The persistence of shocks implies that a firm that receives a positive shock that raises its current profitability \( \tilde{\varphi}_{it} \) will also
expect to be profitable in subsequent periods (i.e. has a high option value). This, coupled with the sunk nature of entry costs, implies that a firm that selects into exporting will be unlikely to exit the foreign market in the first few years after export entry: survival rates are initially high for export entrants and decline over time as the positive shocks that led to export entry die over time. Export entrants will also immediately adjust their exports to the optimal level since there is no other barrier to exporting: the firm immediately exports as much as it can. This implies that the exports of entrants are expected to gradually decline over time as the positive shocks that led to export entry die over time.

At the level of the firm the presence of sunk entry costs and serially correlated shocks to the profitability of exporting firms leads to export entrants that have:

1. High initial survival rates in the export market, with these rates declining over time.

2. High initial export volumes, with export volumes gradually declining over time.

### 2.4.2 Export Dynamics and Firm Participation

In this section I contrast the implications of the framework presented in section 2.4.1 for firm-level dynamics and aggregate patterns against the Mexican firm level data for the period 2000-2007.

Concerning aggregate patterns, the first key implication of the framework of section 2.4.1 is that there is a steady state mass of exporters and that this implies a steady state flow of entry into and exit out of exporting. Table 2.9 presents the number of exporting firms per year and the entry, exit, and survival rates according
to the following definition: at time $t$ I label firms as

$$EXP_t : \text{any firm that exports in year } t$$

$$ENTER_t : \text{a firm that does not export in year } t - 1 \text{ but exports in year } t$$

$$EXIT_t : \text{a firm that exports in year } t - 1 \text{ but does not export in year } t$$

$$CONTINUE_t : \text{a firm that exports in both years } t - 1 \text{ and } t$$

$$SURV_t : \text{a firm that does not export in year } t - 1 \text{ but exports in both years } t \text{ and } t + 1,$$

and from this classification of firms I define the entry, exit, and survival rates as

$$\text{Entry Rate}_t = \frac{\#ENTER_t}{\#EXP_t}$$

$$\text{Exit Rate}_t = \frac{\#EXIT_t}{\#EXP_{t-1}}$$

$$\text{Survival Rate}_t = \frac{\#SURV_t}{\#ENTER_t}.$$

Table 2.9 shows that the number of exporting firms is relatively stable over the sample period, as are the entry, exit, and survival rates of exporters. Notice, however, that there is a slight increase in these numbers starting in 2004. This coincides with a phasing in of tariff reductions with other NAFTA members. Thus, the higher average number of firms, higher average entry rate, higher average survival rates and lower average exit rates post 2004 could be interpreted as the result of a transition to a new steady state with lower trade barriers. Regardless, Table 2.9 is largely consistent with the prediction of a steady state mass of exporting firms, with steady flows into and out of exporting.

The second important prediction of the the framework of section 2.4.1 regarding aggregate patterns is that “continuing” firms should account for most of total exports in any given year and for most of the year-to-year variation. Entering firms should account for a higher share of exports than exiting firms, and both should be expected
Table 2.9: Entry, Exit and Survival Rates

<table>
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<th>Year</th>
<th>2000</th>
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<th>2002</th>
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<th>2004</th>
<th>2005</th>
<th>2006</th>
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<td>No. of Exporters</td>
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<td>34,975</td>
<td>32,506</td>
<td>31,271</td>
<td>35,068</td>
<td>37,345</td>
<td>36,086</td>
<td>35,915</td>
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<td>-</td>
<td>38.2%</td>
<td>37.2%</td>
<td>36.5%</td>
<td>42.2%</td>
<td>39%</td>
<td>35.8%</td>
<td>36.5%</td>
</tr>
<tr>
<td>Exit Rate</td>
<td>-</td>
<td>40.6%</td>
<td>41.6%</td>
<td>38.9%</td>
<td>35.2%</td>
<td>35.1%</td>
<td>38%</td>
<td>36.8%</td>
</tr>
<tr>
<td>Survival Rate</td>
<td>-</td>
<td>35.2%</td>
<td>37.5%</td>
<td>41.8%</td>
<td>43.7%</td>
<td>37.3%</td>
<td>36.5%</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2.9: Entry, Exit and Survival Rates

to export less than incumbent exporters. To this end, I now classify the set of firms active in the export market according to the following three year definition: continuing firms in $t$ are those that exported in $t - 1$, $t$, and $t + 1$; entering firms in $t$ are those that did not export in $t - 1$, and did export in $t$ and $t + 1$; exiting firms in $t$ are those that exported in $t - 1$ and $t$, but not in $t + 1$, and single-year exporters in $t$ are those that exported in $t$, but not in $t - 1$ nor in $t + 1$. Notice that in this case “entering” firms are divided into two classes: those that maintain their export status after the initial export year (entering firms) and those that do not (single-year exporters). The framework of the previous section implies that single-year exporters should represent a relatively small fraction of all the firms that select into exporting at $t$ given the presence of sunk entry costs and the persistence of the shocks faced by the firm.

Table 2.10 presents the share of exporting firms in each of the four categories described, while Table 2.11 presents the share of exports commanded by each category. The share of firms in each category is relatively stable over time. In line with the predictions of section 2.4.1, continuing firms account for the largest share of exports in any given year and entering firms have a higher share in total exports than exiting firms. However, Tables 2.10 and 2.11 show that there is a surprisingly large number of firms that select into exporting, export a small volume and immediately exit from exporting. This large number of single-year firms that enter only to export a small amount is at odds with the predictions from section 2.4.1.

To understand how selection into and out of exporting shape total export growth I decompose total exports to reflect the contributions of continuing firms, entrants,
<table>
<thead>
<tr>
<th>Year</th>
<th>Entering</th>
<th>Continuing</th>
<th>Exiting</th>
<th>Single-Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001</td>
<td>13.46</td>
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<td>2004</td>
<td>18.47</td>
<td>46.46</td>
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<td>2005</td>
<td>14.57</td>
<td>47.47</td>
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</tr>
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<td>2006</td>
<td>13.07</td>
<td>50.16</td>
<td>14.04</td>
<td>22.73</td>
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</table>

Table 2.10: Share of Firms: Entering, Exiting, Continuing and Single-year Exporters

<table>
<thead>
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<th>Year</th>
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<th>Continuing</th>
<th>Exiting</th>
<th>Single-Year</th>
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<td>2002</td>
<td>3.39</td>
<td>95</td>
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<td>0.21</td>
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<td>2003</td>
<td>3.58</td>
<td>93.91</td>
<td>2.17</td>
<td>0.34</td>
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<td>2004</td>
<td>2.85</td>
<td>95.39</td>
<td>1.58</td>
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<td>1.79</td>
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<td>2006</td>
<td>1.60</td>
<td>97.22</td>
<td>0.96</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Table 2.11: Share of Exports: Entering, Exiting, Continuing and Single-year Exporters

and exiters. Thus, I define

\[
CN_{t,t+1} = \text{firms that export in } t \text{ and } t + 1 \text{ (continuing firms)}
\]

\[
EX_{t,t+1} = \text{firms that export in } t \text{ but not } t + 1 \text{ (exiting firms)}
\]

\[
EN_{t,t+1} = \text{firms that export in } t + 1 \text{ but not } t \text{ (entering firms)}
\]

\[
NEX_{t,t+1} = \text{number of exiting firms}
\]

\[
NEN_{t,t+1} = \text{number of entering firms}.
\]
Using these definitions I can decompose export growth as

$$\frac{X_{t+1} - X_t}{(X_t + X_{t+1})/2} = \left( \sum_{j \in CN_{t,t+1}} \frac{[X_{jt} + X_{jt+1}] / 2}{(X_t + X_{t+1}) / 2} \right) - \left( \frac{\sum_{j \in CN_{t,t+1}} [X_{jt+1} - X_{jt}]}{\sum_{j \in CN_{t,t+1}} [X_{jt} + X_{jt+1}] / 2} \right)$$

$$+ \frac{NE_{N_{t,t+1}} \bar{x}_t}{(X_t + X_{t+1}) / 2} + \frac{\sum_{j \in EN_{N_{t,t+1}}} [X_{jt+1} - \bar{x}_t]}{(X_t + X_{t+1}) / 2}$$

$$- \frac{NE_{E_{N_{t,t+1}}}}{(X_t + X_{t+1}) / 2} - \frac{\sum_{j \in EN_{N_{t,t+1}}} [X_{jt} - \bar{x}_t]}{(X_t + X_{t+1}) / 2}$$

where $\bar{x}_t$ denotes average firm exports in year $t$.

The contribution of continuing firms is equal to their share in exports over the two years active times the growth in their sales over those two years. The contribution of entering firms can be decomposed into two terms: the growth in exports implied by the increase in the number of firms if they had the same size as the average firm the previous period, and the difference between the exports of entrants and those of the average firm the previous period. The contribution of exiting firms can be decomposed into two terms in a similar fashion.

Table 2.12 and Figure 2.19 present the growth of aggregate exports and the percentage contribution to growth of total exports of each of the terms in the de-
Figure 2.19: Decomposing Export Growth: Continuing, Entering, and Exiting Firms composition above. It is easily seen that, in line with the predictions of section 2.4.1, continuing firms account for most of the year-to-year variation in total exports. Entry makes a positive contribution to export growth, exit makes a negative contribution to export growth, but in total entry and exit have only a modest effect on the year-to-year variations in total exports.

Column 4 in Table 2.12 shows that the contribution of entering firms to export growth arising from the difference between their exports and those of the average firm the previous period is negative, while column 6 shows that the contribution of exiting firms to export growth arising from the difference between their exports and those of the average firm the previous period is positive. This is consistent with the prediction of section 2.4.1 that both entering and exiting firms have export volumes that are smaller than the average exports of incumbent exporters.

The results presented in Tables 2.9 through 2.12 and Figure 2.19 concerning aggregate export patterns are largely consistent with the predictions of the framework.
for export dynamics presented in section 2.4.1. and consistent with the findings of Eaton et al. [2008] for Colombian firm-level data. However, in contrast to the predictions of section 2.4.1 the data shows that single-year exporters constitute a large fraction of the firms selecting into exporting any given year. These firms enter the export market, sell a small quantity, and immediately exit. This is at odds with the predictions of section 2.4.1 where the presence of sunk entry costs and the persistence of shocks imply that firms that select into exporting will expect to maintain their export status in the periods immediately following their initial entry into exporting. Eaton et al. also find that in Colombia single-year exporters represent a large share of the firms selecting into exporting any given year, but that they account for a small share of total exports. While this feature of the data is at odds with the sunk entry cost model of section 2.4.1, it is consistent with a strand of the literature that emphasizes firm experimentation that finds that many firms experiment by exporting during brief periods of time and doing so at a small scale (see Rauch and Watson [2003] and Akhmetova and Maritonna [2013]).

2.4.3 Firm-Level Export Supply Dynamics

In section 2.4.1 the main prediction regarding the dynamics of firm-level export supply was that new exporters should exhibit high initial survival rates, with these rates declining over time, and an immediate adjustment to a full-scale of operation in the export market, with a gradual decrease in export sales as the positive shocks that led to export entry die over time. I now contrast these predictions against the data.

I begin by analyzing the evolution of cohorts of new exporters as they age in the export market. I assign a firm to cohort $t$ if the first report of an export transaction by that firm over the period of study occurs in year $t$. I then track how cohort $t$ evolves in the years following export entry. During the period 2001-2007, the typical cohort of new export entrants consisted of roughly 13,000 firms. Tables 2.13 and 2.14
First year of report between 2001 and 2007

<table>
<thead>
<tr>
<th>Year</th>
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<td>24.30</td>
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Table 2.13: Fraction of Cohort Active by Initial Export Year Cohorts

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<th>2006</th>
<th>2007</th>
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<td>5.55</td>
<td>3.50</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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<tr>
<td>2003</td>
<td>5.99</td>
<td>5.01</td>
<td>3.73</td>
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<td>0</td>
</tr>
<tr>
<td>2004</td>
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<td>5.97</td>
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<td>0</td>
</tr>
<tr>
<td>2007</td>
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<td>5.33</td>
<td>6.06</td>
<td>3.38</td>
<td>2.92</td>
<td>2.49</td>
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</tbody>
</table>

Table 2.14: Share in Total Exports by Initial Export Year Cohorts (%)

present the results for the evolution of fraction of the cohort that is active\(^{26}\) and the share of the cohort in total exports. Differences across cohorts may be the result of entering into exporting in better (worse) than average years. However, the patterns do not vary substantially across cohorts.

Consistent with the finding on single-year exporters reported in Table 2.10, Table 2.13 shows that in every cohort of new export entrants there is a large fraction of entrants that do not maintain their export status in the year following export entry. It can also be seen that there is a gradual thinning of the members of the cohort that are active in the export market and that their share in total exports grows between entry and the subsequent period: the share of a cohort in total export grows by roughly 60% between the year of entry and the following year.

\(^{26}\text{By considering the fraction of the initial cohort that is active at } t, \text{ re-entry is not precluded.}\)
Since Tables 2.13 and 2.14 do not control for re-entry into exporting by cohort members that had previously exited, Figure 2.20 presents the dynamics of new export entrants *conditional on survival*. For brevity I present results for the 2001 cohort, but note that the 2002-2005 cohorts display similar patterns. Figure 2.20 is strikingly at odds with the predictions of section 2.4.1 for the dynamics of firm-level export supply. In the data new export entrants have low initial survival rates that gradually grow over time and their exports also show a gradual increase as they gain experience in the export market. The patterns in the data for firm-level dynamics are exactly the opposite to what is predicted by the framework presented in section 2.4.1. This is consistent with the finding of Ruhl and Willis [2014] for Colombian firm-level data.

To see that the growth in average export sales depicted in Figure 2.20 is not entirely due to the effect of the selection out of exporting of smaller firms, Figure 2.21 presents the dynamics of average export sales for a subset of firms that maintained a continued export presence throughout the sample period (i.e. exported every year from 2001 through 2007). I dub this set of exporters “long-term survivors” and Figure 2.21 shows that even within this subset of firms there is gradual growth in export sales following export entry (for ease of comparison the relevant panel from Figure 2.20 is also presented in Figure 2.21). While the predictions of section 2.4.1 regarding
aggregate patterns are largely confirmed in the data, at the firm-level the dynamics of export supply are strikingly at odds with the predictions of the sunk entry cost model of section 2.4.1.

### 2.4.4 The Rise of Multi-Product, Multi-Destination Firms

In section 2.4.3 it was shown that, in contrast to the predictions of section 2.4.1, firms undergo a gradual process of growth in the foreign market after export entry. In this section I focus on the evolution of new export entrants to understand how firms grow and develop their presence in foreign markets. The three-dimensional nature of the Mexican transaction-level data (covering two extensive margins and one intensive margin) allows me to provide a rich account of the transition of new export entrants as they undergo their process of internationalization. In particular, it allows me to shed light on the evolution of new export entrants into the kind of multi-product, multi-destination firms that dominate aggregate trade.

To emphasize the transition of firms from new export entrants into mature exporters I focus on the evolution of the set of “long-term survivors” from the 2001 cohort. By doing so I am able to abstract from the selection forces that influence cohort dynamics. For this set of exporters I ask: How did the extensive margins
(number of products and number of destinations) and intensive margin evolve after export entry?

Table 2.15 presents results comparing the average long-term survivor against the average active firm in the cohort for the duration of the sample period across a number of dimensions.\(^{27}\) Table 2.15 shows that even after the strong selection of the first year has kicked in, long-term survivors are significantly bigger than other cohort members: their sales are always at least twice as big, they export to at least 30% more destinations, and they export at least 45% more products. However, Table 2.15 also shows that as surviving firms mature in the export market they close the gap with respect to long-term survivors along all dimensions.

Table 2.16 presents the evolution of the 2001 cohort of long-term survivors. After surviving the first export year firms expand rapidly and continue to grow, but at decreasing rates. The growth rate in the first year after beginning to export is orders of magnitude greater than subsequent growth. Even if we exclude the first-year growth rate on account of partial year effects (see Bernard et al. [2014]) and consider 2002 as the first-full year of export activity, export growth between 2002 and 2003 is nearly twice that of the subsequent year.

In section 2.3.2 it was shown that most of exports are accounted for by a relatively small number of multi-product multi-destination firms. Figures 2.22 and 2.23 show the evolution of the distributions of number of destinations reached and number of

\(^{27}\)Long-term success in the export market is significantly related to size upon entry. A logistic regression for the outcome of becoming a long-term survivor, regressed on first-year sales, reveals that increasing first-year sales by one-standard deviation is associated with 20% higher odds of becoming a long-term survivor.
Table 2.16: Dynamics of Long-term Survivors

* Millions of US dollars. Intensive = Sales per Destination per Product. Growth Sales_1 = 100 * (ln X_{t+1} - ln X_t). Growth Sales_2 = 100 * \left( \frac{X_{t+1} - X_t}{(X_{t+1} + X_t)/2} \right)

Figure 2.22: Distribution of Number of Destinations for Long-Term Survivors

products exported for the group of "long-term" survivors. To visualize the results more clearly, only the distributions for 2001, 2004, and 2007 are plotted. However, the omitted distributions align neatly between the ones depicted and thus, to a first-approximation, the distribution of number of export destinations in \( t + 1 \) first-order stochastically dominates the distribution of number of export destinations in \( t \). The same is true for the distribution of number of products. That is, as long-term survivors gain experience in the export market it becomes increasingly likely that they will export more products and reach more destinations.

In 2001, 77% of exporters started their export experience by serving only one market, 15% started by serving 2 or 3 markets, and 8% started exporting with 4
or more destinations. These numbers are similar to those found by Albornoz et al. [2012] for first-time Argentinian exporters. Within the group of single-destination first-time exporters, 84% started their export experience by exporting to the US, 2% by exporting to Guatemala, and 1.7% by exporting to Canada. These numbers are consistent with findings elsewhere in the literature that find that firms that only serve a small number of export markets tend to sell to the most popular ones, with less popular export destinations served almost exclusively by firms that export very widely. By 2007, only 60% of these “long-term” survivors remained single destination exporters, 22% served 2 or 3 destinations, and 18% served 4 or more destinations. Similarly, in 2001 48% of firms started their export experience by exporting one product, 28% by exporting 2 or 3 products, and 14% by exporting 4 or more products. By 2007, only 28% of “long-term” survivors were single-product exporters, while 20% now exported 2 or 3 products, and 52% exported 4 or more products.

To gain insight into the pattern of expansion of firms in export markets I investigate the way in which “long-term” survivors expand their presence in foreign markets by classifying their transactions into four categories: 

(i) old products in old destinations: these are transactions that the firm carried out both at $t - 1$ and
old products in new destinations: these are transactions in which firms, at time $t$, introduce products that they were selling at $t - 1$ into destinations where these products were not being sold at $t - 1$; (iii) new products in old destinations: these are transactions in which firms, at time $t$, introduce into destinations which had been reached at $t - 1$ products that they were not selling in those destinations at $t - 1$, and (iv) new products in new destinations: these transactions correspond to products which the firm was not selling anywhere at time $t - 1$ and doing so in destinations the firm did not reach at $t - 1$.

Table 2.17 present the results for the the participation of each category in the total number of transactions. These numbers show that after the initial export year, the extensive margin for “long-term” survivors adjusts rapidly with over 60% of transactions being new transactions for the firm. In particular, after surviving the initial export year firms expand rapidly through the introduction of new products into destinations served during the initial year of the firm’s export tenure: in the second year of a “long-term” survivor’s tenure the introduction of new products into old destinations accounts for 40% of all transaction and 10% of export value.

The results in Table 2.17 also show that young exporters engage in some “experimentation” in foreign markets (see Akhmetova and Mitaritonna [2013]) by introducing new products into new destinations (i.e. transactions in which they have no previous experience). These type of transactions represent a negligible share of export value, and is consistent with the idea advanced by Rauch and Watson [2003] that firms may start out small in unfamiliar environments.
Table 2.17: Sources of Exports for Long-Term Survivors (% of no. of transactions)

To gain further insight into how these different types of transactions contribute to the expansion of “long-term” survivors in foreign markets, for firm $i$ at time $t$ I define

\[ X_{it} : \text{exports} \]
\[ T_{it} : \text{no. of transactions} \]
\[ x_{it} : \text{average value of a transaction} \]
\[ o_{it} : \text{old transactions of firm} \]
\[ p_{it} : \text{transactions where new products are introduced in old destinations} \]
\[ d_{it} : \text{transactions where old products are introduced in new destinations} \]
\[ n_{it} : \text{new products introduced in new destinations} \]

Using this notation firm exports can be expressed as $X_{it} = T_{it}x_{it}$ and its transactions as $T_{it} = o_{it} + p_{it} + d_{it} + n_{it}$, which forms the basis for the following decomposition of export growth:

\[ X_{it+1} - X_{it} = T_{it+1}x_{it+1} - T_{it}x_{it} \]
\[ = [o_{it+1} + p_{it+1} + d_{it+1} + n_{it+1}]x_{it+1} - T_{it}x_{it} \]
\[ = o_{it+1}[x_{it+1} - x_{it}] + p_{it+1}x_{it+1} + d_{it+1}x_{it+1} + n_{it+1}x_{it+1} - \delta_{it}x_{it}, \]

where $\delta_{it} = T_{it} - o_{it+1}$ denotes the number of relationships of firm $i$ that ended at time $t$. Using the above decomposition I account for the contribution of each of these
The results are reported in Table 2.18. The introduction of new products into destinations that the firm had already served in previous years is quantitatively the most important source of growth for “long-term” survivors. This implies that firms do not enter an export market with the full range of products that, conditional on survival, they will eventually sell in that destination: the product mix of exporters in a given destination evolves over time. Furthermore, changes in the product mix of new export entrants are not necessarily due to trade liberalizations that would reduce barriers leading firms to expand their product range in destinations they were already serving: both in 2002 and 2003 -before the phasing in of the trade liberalization with other NAFTA members that Mexico experienced- the margin of “new products in old destinations” was quantitatively the most important source of export growth for “long-term” survivors.

The fact that young exporters keep adding products to destinations they already served suggests that they face constraints that restrain their export presence in these markets. This pattern of gradual growth can be consistent with both the idea of financial frictions that become less important over time as the firm accumulates assets and with the idea that young firms undergo a process of self-discovery in the export

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<th>2005</th>
<th>2006</th>
<th>2007</th>
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<td>-120.84</td>
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<td>-125.19</td>
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<td>461.88</td>
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</tbody>
</table>

Table 2.18: Contribution of Different Transactions to the Export Growth of Long-Term Survivors (%)
market and that as they gather information regarding their ability to profitably serve the foreign market they gradually expand.

Finally, I consider the entry process of “long-term” survivors into new destinations. In section 2.2 it was advanced that, in principle, the “barriers to exporting” could result in a hierarchy for export destinations in the sense that, more often than not, any firm selling to the $k + 1^{th}$ most popular destination necessarily sells to the $k^{th}$ most popular destination. The evidence presented in section 2.3.1 was consistent with this idea in that it was shown that a country’s “barriers” to exporting are strongly correlated with the share it commands in Mexican exports. Eaton et al. [2011], using data for French exporting firms, find evidence for such a hierarchy for export destinations. On the other hand, the evidence presented in Table 2.16 and Figure 2.22 shows that firms gradually add destinations to their export portfolio.

This suggests that new export entrants enter new destinations sequentially and they do so according to the hierarchy defined by the barriers to exporting.

From the group of “long-term” survivors I now consider the subset of exporters that started as single destination exporters and track their entry process into new export markets. Table 2.19 shows the average barriers to exporting for newly added destinations as firms gain experience in the export market. It is clear that destinations that are added later on in the firm’s tenure are, on average, destinations that are harder to breach. These results are consistent with the idea that firms enter markets sequentially and they do so according to the market hierarchy defined by the barriers to exporting. Furthermore, Figure 2.24 reports the average first-year growth rate, conditional on survival, for sequential markets being served by the firm. From the second period onwards, the reported growth rate groups the sales to all destinations.

\footnote{Eaton et al. [2008a], using data for Colombian exporters, also find that new export entrants typically begin in a single foreign market and, conditional on survival, gradually expand into additional destinations.}

\footnote{Out of these first-time single destination exporters, 84% started in the United States, Mexico’s top export destination. The rest started in either Canada or Guatemala that are also top export destinations for Mexican exporters.}
<table>
<thead>
<tr>
<th>Years since Export Entry</th>
<th>Average Barriers to Exporting for Newly Added Destinations</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>104.19</td>
</tr>
<tr>
<td>1</td>
<td>128.20</td>
</tr>
<tr>
<td>2</td>
<td>131.44</td>
</tr>
<tr>
<td>3</td>
<td>131.53</td>
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<tr>
<td>4</td>
<td>133.93</td>
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<tr>
<td>5</td>
<td>134.96</td>
</tr>
<tr>
<td>6</td>
<td>135.19</td>
</tr>
</tbody>
</table>

Table 2.19: Sequential Exporting and Market Hierarchy

Figure 2.24: Sequential Exporting (Average First-year Growth Rates, Conditional on Survival)

A striking feature of Figure 2.24 is that first-year growth rates, conditional on survival, are decreasing for export destinations that are added later in the firm’s tenure as an exporter.

Albornoz et al. [2012] find a similar pattern to that presented in Figure 2.24 for Argentinian exporters. This pattern, together with the general decrease in the growth rates of export sales for surviving firms is taken by these authors as suggestive of the importance of learning, through the resolution of uncertainty that occurs when a firm

\[30\] On average, this subset of firms only add 1 or 2 destinations at a time.
decides to engage in international trade, as an important force shaping the dynamics of firm expansion in foreign markets.

Figures 2.20, 2.22, 2.23, and 2.24 depict a process of gradual expansion in foreign markets for successful export entrants. These features of the data suggest that learning in export markets can be an important determinant of the export supply decisions of new export entrants. The role of self-discovery in shaping new exporter dynamics is the subject of chapter 3, where I formalize the learning process that firms undergo in the export market in a dynamic setup similar to the framework of section 2.4.1.

2.5 Conclusions

This chapter provides a dissection of the role that firms play in mediating Mexican exports. The three-dimensional nature of the data, two extensive margins and one intensive, allow for a rich characterization of the participation of Mexican firms in international markets. The data is contrasted against the predictions of models of export supply featuring heterogeneous firms. It is shown that in the cross-section, the distribution of exports across export destinations and across firms is consistent with the multi-product, multi-destination frameworks developed by Bernard et al. [2011] and Mayer et al. [2014]. However, concerning the dynamics of export supply featuring heterogenous firms, it is shown that the data largely supports the predictions of the benchmark model for aggregate patterns, but that the model’s predictions for the dynamics of firm-level export supply are not supported by the data. Additionally, the data reveal that firms that select into exporting only to immediately exit are more prevalent than what the model would suggest.

In addition, this chapter also provides a richer account of the dynamics of new export entrants than what is available in the literature. Currently there are two
robust stylized facts concerning new export entrants: 1. their continuation rates in the export market, conditional on survival, are increasing with export tenure, and 2. conditional on survival, the growth rate of export sales are decreasing with export tenure (see Besedes and Prussa [2011], Ruhl and Willis [2014], and Kohn et al. [2015]). I confirm these patterns in the Mexican firm-level data and in addition document the gradual expansion of surviving entrants in terms of number of products exported and number of destinations served, and quantify the importance of these margins in explaining the growth of new export entrants. The process of gradual expansion along all margins of adjustment for new export entrants can be accounted for by a process of self-discovery regarding a firm attribute that has global scope and that is initially unknown to the firm as suggested by Albornoz et al. [2012]. The formalization of these learning dynamics and their role in accounting for the patterns displayed in Figure 2.20 are the subject of chapter 3.

Bibliography


Chapter 3

Learning and Firm Exporter Dynamics

3.1 Introduction

What explains the internationalization process of new export entrants? The extensive margin of entrants into export markets plays an important role in export booms (see Roberts and Tybout [1997]). In chapter 2 it was shown that new exporters exhibit a Darwinian process of selection with high rates of exit and rapid growth conditional on survival. Conditional on survival, exporters undergo a period of adjustment in their foreign market presence lasting several years as they transition from new to mature exporters. Export supply responsiveness is of central importance to policymakers who often tie the success of structural adjustment programs to the extent to which strong export responses follow these reforms. Structural models of export supply with microeconomic foundations provide a useful framework to study the dynamics of firm level trade and to evaluate the impact of trade policy on aggregate trade volumes.

\footnote{Besedes and Prusa [2011] find that 70\% of new export relationships fail within the first two years.}
The dynamics of new export entrants in structural models of export supply à la Melitz such as Das et al. [2007] and Ruhl and Willis [2014], that focus on the role of sunk entry costs, producer heterogeneity and exchange rate movements on the dynamics of exporting firms, are at odds with the dynamics of new exporters observed in the data. In these models exporters grow too large too quickly and survive for too long. By generating new exporters that live too long and export too much, these class of models provide an inaccurate depiction of the importance of the contribution of the extensive margin of entrants in aggregate trade growth and fail to capture the dynamics of internationalization that new exporters go through in the process of establishing a secure foreign market presence. As such, a deeper understanding of the microeconomic foundations of export supply is needed to understand the dynamics of firm level trade and to properly assess the contribution of export entrants in aggregate export growth.

In this chapter I take up a point raised in section 3 of chapter 2, and develop a model of export supply based on Melitz [2003] in which firm dynamics are driven by the process of self-discovery that new exporters undergo in foreign markets. These learning dynamics are as in the industry equilibrium model of Jovanovic [1982].

Self-discovery in the export market will lead to a model with “noisy” selection into exporting and where a firm’s tenure in the export market is the firm characteristic determining growth and survival in the foreign market. I structurally estimate the model using transaction-level customs data for Mexican exporters and show that

\[ \text{In this class of models the interaction between sunk entry costs and other factors determining the profitability of the firm are key in understanding the failure of the model to account for high failure rates and the gradual expansion of new exporters. The failure to generate a gradual increase in exports stems from that fact that, upon entry, a new exporter immediately adjusts its exports to the optimal level since there are no other barriers to exporting (i.e. once the plant pays the sunk entry costs it exports as much as it can). On the other hand, the model’s failure to deliver high exit rates early on in the tenure of a new exporter results from the interaction between sunk entry costs and the persistent nature of productivity and exchange rate shocks: sunk entry costs generate an option value to exporting, thus selection is based not only on current profitability, but also on future profitability. When firms face a positive shock to their profitability, the persistent nature of these shocks implies that the firms that enter the export market will be the most profitable and the least likely to exit in the subsequent periods (see Ruhl and Willis [2014] for details).} \]
the estimated model accounts both qualitatively and quantitatively for the observed patterns of export dynamics of new exporters observed in the data.

I use the estimated model to quantify the role of learning in shaping the dynamics of export supply. Little is known about the time span of foreign market unfamiliarity. When export entrants perceive their own lack of foreign-market knowledge, how long does it take them to remedy this situation? The structural model allows me to address questions such as: How fast do firms learn their way out of the uncertainty they face in the foreign market? How does the option value generated by self-discovery shape the export supply decision of firms relative to a purely static model of export supply such as Melitz [2003]? Additionally, the model also provides a framework that can be used to undertake counterfactuals for the effects of export promotion on aggregate trade.

In contrast to models that highlight sunk entry costs and production heterogeneity (see Das et al. [2007]), this model gives prominence to self-discovery as a key determinant of the export supply responsiveness of new exporters. Export promotion agencies (EPAs) often argue that limited information about foreign markets represents an important barrier to the internationalization process of new export entrants.\(^3\) Survey evidence supports this view. In a survey of non-exporting members of the Turkish Chamber of Commerce, Karakaya and Harcar [1999] found that “lack of information about foreign markets” was the most important external barrier to exporting perceived by respondents. Jalali [2012] and Kneller and Pisu [2011] find similar results in surveys of Greek and UK firms, respectively. Interestingly, the latter study finds that after two years of experience in the export market half of the responding firms no longer

\(^3\)For example, the UK Department for International Development writes

“Entering a new market is an inherently more risky and uncertain process for a firm than operating in a market in which it is already established...qualitative research suggests that prior to investigating overseas markets some firms underestimate the potential demand for their product or services in overseas markets.”
perceived “lack of information about foreign markets” as a barrier to their export activities.

For domestic markets, recent studies have found that unfamiliarity with demand conditions can account for the observed differences between firms of different ages. For U.S. manufacturing plants Foster et al. [2012] argue that the observed size differences between young and old plants are unlikely to be the results of productivity differences. These authors find that physical TFP levels of new plants are slightly higher than those of incumbents and that TFP differences vanish by the time plants are five years old. On the other hand, they document important differences in the idiosyncratic demands faced by plants: at the same price a new plant will sell only 58% of the output of a plant in the same industry that is more than 15 years old. These authors find evidence that lends support to a model featuring dynamic demand-side forces that lead to the accumulation of relationship capital along buyer-supplier links that leads to the gradual growth of entrants (conditional on survival). Furthermore, the uncertainties tied to such processes create an option value of waiting to expand until further information about demand is revealed. A model of “learning” about demand would be consistent with these findings. The dynamics that differentiate young and old plants may also apply to the dynamics that distinguish new and established exporters. Thus, “learning” about conditions in the foreign market could help understand the gradual adjustment in the foreign market presence of new exporters. In the international context, Artopoulos et al. [2013] conducted a study of Argentinian exporters in four selected industries that experienced episodes of export emergence and found that foreign market knowledge was a critical constraint to achieving consistent exports. In fact, these authors find that it is a lack of foreign market knowledge rather than a lack of production knowledge that inhibits firms from developing an established export presence in foreign markets.
The model developed in this paper features self-discovery as the driving force shaping the dynamic behavior of export entrants. The evolution of a firm’s beliefs regarding its “export profitability” is the key determinant of the firm’s expansion in foreign markets. Expectations concerning export profitability will affect a firm’s calculations regarding whether future export profits will cover the costs of maintaining a foreign market presence or not. In fact, all the dynamics in the model will be driven by the learning process that firms undergo and the state dependence that this process generates through the firm’s information sets. However, this force shaping export dynamics will be decreasing in importance with export tenure as firms uncover their true export profitability.

The main results that I obtain from the estimated model and counterfactuals are: 

(i) first-time exporters expect to incur losses by serving the foreign market, but the option value generated by the acquisition of more precise information regarding export profitability compensates inexperienced exporters for these losses; 

(ii) the initial period serving the foreign market provides a crucial learning experience for new exporters, but the discovery stage extends beyond the first year: the value of learning remains positive for the first four years of tenure in the export market. The probability of exiting the export market decreases with tenure and after the discovery stage is only 5% higher than the exit probability of well established exporters; the cutoff for exporting experiences 90% of its long-term adjustment over the same period; 

(iii) firms that continuously export over a period of six years observe a 137% increase in their (ex ante) probability of serving the foreign market and a 900% increase in their (average) export premia, and 

(iv) temporary shocks to the profitability of serving the export market can have permanent consequences on aggregate trade volumes. In particular, export promotion policies that temporarily subsidize the fixed costs of maintaining a presence in the foreign market can result in permanent increases in
aggregate trade volumes. The impact of these types of policies crucially depends on the speed at which firms are able to uncover their export profitability.

My work is related to a recent literature that has exploited firm- and plant-level data to uncover a set of stylized facts for exporters (see, for example, Eaton et al. [2011] and Bernard et al. [2012]). This paper is related to the work of Arkolakis [2010], Ruhl and Willis [2008], and Alessandria et al. [2013] which study the dynamics of new export entrants. However, rather than focusing on the cost structure faced by firms as these authors have done, I focus on the role of demand side uncertainties on export decisions. Akhmetova and Mitaritonna [2013] also study the effects of demand side uncertainties on exporter behavior, but their focus is on the choice of technology used to serve the foreign market while the focus here is on the observed relationship between growth, survival and export tenure for new export entrants.

This paper is closely related to a research program advocated by Arkolakis and Papageorgiou [2009] and to the work of Albornoz et al. [2012]. The latter provides reduced form evidence in support of the claim that when firms face ex-ante uncertainty regarding the profitability of serving the export market, shortcomings at the discovery stage are an important explanation for the limited export success of some developing countries. In contrast to these authors my approach is structural and allows me to quantify the role played by self-discovery in shaping the export supply decision of new exporters.

This model studied here is also related to the work of Arkolakis [2013] who studies the dynamics of selection and growth in a general equilibrium model of international trade. Here, however, given that self-discovery is the driving force behind firm dynamics in the foreign market it is export tenure rather than size that determines the opportunities for growth and survival. Finally, my work also relates to the dynamic structural models of export supply of Das et al. [2007] and Morales et al. [2014] which structurally estimate micro-founded models of export dynamics. Das et al. focus on
the firm level dynamics implied by sunk entry costs and production heterogeneity and their consequences for aggregate trade in response to devaluations and export subsidies. Morales et al. focus on the dynamics of the extensive margin of destinations served and study “extended gravity” forces that lead exporting firms to enter foreign markets that are similar to markets previously served. In contrast, the focus here is on the firm level dynamics implied by demand-side uncertainties and the adjustment of firms along the intensive margin of trade.

The rest of the chapter is organized as follows. Section 2 documents the dynamics of new export entrants that motivate the rest of the paper using Mexican micro data. Section 3 develops a model of export-supply featuring self-discovery, and Section 4 describes the estimation approach and presents the results from estimation. Section 5 uses the estimated model to quantify the role of self-discovery in the export supply decisions of new exporters, and Section 6 uses the model to perform counterfactuals regarding export promotion and the speed of learning. Section 7 concludes.

3.2 New Exporter Dynamics

Micro-level trade data reveal that new exporters experience a substantial amount of adjustment that continues after entry into export markets. In this section I document the dynamics of new exporters as they transition from new to experienced exporters that are the focus of this chapter.

In chapter 2 it was established that the cross-sectional features of the Mexican transactions-level trade data are consistent with the stylized facts that have informed trade models over the last decade that emphasize the importance of selection into exporting to account for the patterns observed in transaction-level trade data. Further details regarding the cross-sectional features of the Mexican trade data can be found in chapter 2.
I concentrate my attention on the cohort of exporters whose first period reporting positive exports is 2001 (i.e. “new” exporters) and track the outcomes of these firms over the 2001-2007 period. This is the cohort of new export entrants for which the longest time series is available in the data set.

Figure 3.2.1 documents two prominent features of new exporter dynamics present in the Mexican firm-level trade data: panel (a) documents that continuation rates are increasing with tenure, while panel (b) documents the decreasing average growth of export sales for a subset of firms that maintained a continued export presence throughout 2001-2007. Ruhl and Willis [2014] and Leibovici et al. [2015] document similar patterns for Colombian and Chilean firm-level trade data respectively. Besedes and Prusa [2011] also document continuation rates that are increasing in export tenure in a sample of disaggregated bilateral manufacturing exports for 46 countries for the period 1975-2003.

Figures 3.2.1 suggest that the internationalization process of new export entrants is a gradual process with substantial risk of failure early in the firm’s export tenure. In what follows I show that introducing self-discovery into an otherwise standard model of export supply goes a long way in explaining the features of the data presented in this section. Furthermore, I use the model to quantify the importance of learning in the export supply decisions of new exporters.

### 3.3 An Empirical Model of Export Supply with Self-Discovery

In this section I present a model of export supply that introduces firm learning into an otherwise standard trade model in a way that is both tractable and amenable.

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4By focusing on the subset of exporters who maintained a continued export presence throughout the sample period we can see the effect of tenure on average growth absent selection effects.
Figure 3.1: New Exporter Dynamics

(a) Exporter Continuation Rate

(b) Average Growth Dynamics
to estimation. As such, the model will rely heavily on several key assumptions. First, I start with what has become by now a standard framework for studying the export supply decision (see Melitz [2003] and Bernard et al. [2011]). The domestic and export markets are assumed to be segmented and monopolistically competitive. Specifically, I assume that the demand side of the economy is described by underlying CES preferences that lead to the following revenue functions for the firm\(^5\):

\[
\begin{align*}
\text{(Domestic Revenues)} & : r(q_t) = q_t^{\sigma - 1} \\
\text{(Export Revenues)} & : r^*(q^*_t) = h(\theta_t) q_t^{\sigma - 1}.
\end{align*}
\]

For simplicity I assume that in the domestic market firms face no aggregate or idiosyncratic uncertainty and normalize the demand shifter to unity.\(^6\) In the export market all the uncertainty faced by the firm is idiosyncratic uncertainty regarding its export profitability\(^7\) that is captured through the term \(\theta_t\) that is unknown to the firm. That is, firms face uncertainty regarding the strength of demand for their product in the foreign market. The function \(h : \mathbb{R} \to \mathbb{R}^+\) is assumed to be continuous and bounded.\(^8\)

The analysis here focuses on the microeconomic foundations of the dynamic behavior of firm level export supply decisions. Thus, I abstract from general equilibrium effects by focusing on the firm level export supply decision taking the demand shifter in the foreign market as given. Implicitly, the demand shifter \(h(\cdot)\) is absorbing the aggregate demand shifter in the foreign market.\(^9\)

---

\(^5\)A firm is a producer of one of the differentiated varieties available for consumption in the economy.

\(^6\)This simplification highlights that the focus here is on domestically established firms that have the potential to export, but have not yet started to do so.

\(^7\)I refer to “export profitability” as the firm’s potential to earn revenues in the foreign market.

\(^8\)The representation of the firm’s dynamic optimization problem through the functional equation defined by the Bellman operator necessitates the period return function to be bounded in the firm’s state variables. Restricting \(h(\cdot)\) to be bounded guarantees that the firm’s period return function is bounded in the relevant state variables.

\(^9\)These firms are measure zero and take demand shifters in the home and foreign market as given. The demand shifter is normalized to unity in the domestic market. In general equilibrium
The analysis here focuses on the microeconomic foundations of the dynamic behavior of firm level export supply decisions. Thus, I abstract from general equilibrium effects by focusing on the firm level export supply decision taking the demand shifter in the foreign market as given. Implicitly, the demand shifter \( h(\cdot) \) is absorbing the aggregate demand shifter in the foreign market.\(^{10}\)

I assume that

\[
\theta_t = \theta + \varepsilon_t,
\]

where \( \varepsilon_t \sim i.i.d. N(0, \nu_\varepsilon) \) are firm specific shocks, independent over time and across firms. \( \theta \) is the firm’s “fundamental export profitability”, a persistent component affecting foreign market revenues. I specify the stochastic process for \( \{\theta_t\} \) in this way because this specification provides a tractable way to introduce transitory and permanent, but unknown, components affecting firm revenues into a standard trade model.

The distribution of “fundamental export profitabilities” among the potential entrants is known to all (common prior), but no firm knows what its true export profitability is. That is, an export entrant only knows that \( \theta \) is a random draw from a normal distribution with mean \( \mu_\theta \) and precision \( \nu_\theta.\(^{11}\) A firm also knows the variance of \( \varepsilon \), as well as the exact functional form of \( h(\cdot) \) so that this “prior” distribution is updated as evidence comes in.

---

10These firms are measure zero and take demand shifters in the home and foreign market as given. The demand shifter is normalized to unity in the domestic market. In general equilibrium the demand shifter in the foreign market would be determined by: (a) aggregate expenditures on foreign goods and (b) price indices. The function \( h(\cdot) \) can be time varying, \( h_t(\cdot) \), the important thing is that the firm knows the exact form of the demand shifter in the foreign market, but not the realization of \( \theta.\)

11For convenience when studying the firm’s signal extraction problem I parametrize \( \varepsilon \) and \( \theta \) in terms of their “precision” rather than their standard deviation. That is, \( \nu_\varepsilon = 1/\sigma_\varepsilon^2 \) and \( \nu_\theta = 1/\sigma_\theta^2 \), where \( \sigma_\varepsilon^2 \) is the standard deviation for \( \varepsilon \) and \( \sigma_\theta^2 \) is the standard deviation of the distribution characterizing the (common) prior beliefs of firms.
3.3.1 Firm’s Static Profit Maximization Problem

In this section I describe the firm’s static profit maximization problem. Conditional on $\theta_t$ and the firm’s export status, total firm revenues are given by

$$r_t = \frac{y_t^{\frac{\sigma-1}{\sigma}}} + d_t h(\theta_t) y_t^{\frac{\sigma-1}{\sigma}},$$

where

$$d_t = \begin{cases} 
1 & \text{if the firm exports in period } t \\
0 & \text{otherwise,} 
\end{cases}$$

and $y_t$ and $y_t^*$ are the quantities supplied (and sold) by the firm in the domestic and foreign markets, respectively.

Conditional on export status, profit maximizing firms will equate marginal revenues at home and abroad:

$$y^*_t = d_t [h(\theta_t)]^\sigma y_t.$$

I define $\tilde{y}_t = y_t + y_t^*$, the firm’s total output. Then, total output can be expressed as $\tilde{y}_t = [1 + d_t (h(\theta_t))^\sigma] y_t$, and I can write the firm’s revenues in terms of its scale of operation as

$$r_t = (1 + d_t (h(\theta_t))^\sigma)^{\frac{1}{\sigma}} \tilde{y}_t^{\frac{\sigma-1}{\sigma}}.$$

Let $f$ denote the fixed costs of production (paid in units of domestic output) and let $f_x$ denote the fixed costs of exporting. Conditional on $\theta_t$ and the firm’s export status, firm’s choose their optimal scale of operation to maximize profits:

$$\max_{\tilde{y}_t} \left\{ (1 + d_t (h(\theta_t))^\sigma)^{\frac{1}{\sigma}} \tilde{y}_t^{\frac{\sigma-1}{\sigma}} - (f + d_t f_x + \tilde{y}_t) \right\}.$$

The CES assumption on the demand side allows me to assume that there are no productivity differences between firms and that all heterogeneity is captured through
heterogeneity in the underlying “export profitability” of firms (i.e. heterogeneity in \( \theta \), under the CES assumption, is isomorphic to productivity heterogeneity).\(^\text{12}\) Firms face a constant marginal cost of production (normalized to unity so that the numeraire is the cost of one unit of output), which implies that the decision to serve each market is separable on the cost side. Therefore, the firm’s profit maximizing scale of operation, conditional on \( \theta_t \) and the firm’s export status, is given by

\[
\tilde{y}_t = \left( \frac{\sigma - 1}{\sigma} \right)^\sigma \left( 1 + d_t \left( h(\theta_t) \right)^\sigma \right).
\]

Using this expression for the optimal scale of operation I can express firm profits, conditional on \( \theta_t \) and export status, as

\[
\Pi(d_t|\theta_t) = \left( \frac{1}{\sigma} \left( \frac{\sigma - 1}{\sigma} \right)^{\sigma - 1} - f \right) + d_t \left( \frac{1}{\sigma} \left( \frac{\sigma - 1}{\sigma} \right)^{\sigma - 1} \left[ h(\theta_t) \right]^\sigma - f_x \right).
\]

Taking the expectation over the conditional distribution of \( \theta_t \), the firm’s expected profits are given by

\[
\Pi(d_t) = \left( \frac{1}{\sigma} \left( \frac{\sigma - 1}{\sigma} \right)^{\sigma - 1} - f \right) + d_t \left( \frac{1}{\sigma} \left( \frac{\sigma - 1}{\sigma} \right)^{\sigma - 1} \mathbb{E}[(h(\theta_t))^\sigma | \mathcal{I}_t] - f_x \right),
\]

where \( \mathcal{I}_t \) denotes the firm’s information set at the outset of period \( t \).

In what follows it will prove useful to define \( A_t := (\mathbb{E}[(h(\theta_t))^\sigma | \mathcal{I}_t])^{\frac{1}{\sigma}} \). Using this notation it can be shown that a modified certainty-equivalence result holds: the firm’s optimal export status decision and optimal scale of operation is the same as that of a firm that replaces the unknown \( h(\theta_t) \) by its risk-adjusted expected value \( A_t \) and then proceeds as if there were no uncertainty.\(^\text{13}\)

\(^{12}\)However, one key feature of demand as opposed to productivity is that it is likely to be market specific. This is relevant here as I am looking at the decision of domestic firms to enter a second market (the export market).

\(^{13}\)I refer to \( A_t \) as the risk-adjusted expected value in analogy to its usage in non-expected utility theory where utility \( U_t \) is defined recursively as the solution to the non-linear stochastic difference
With this notation I can express the firm’s optimal scale of operation in the export market as
\[ y_t^* = d_t \left( \frac{\sigma - 1}{\sigma} \right)^\sigma A_t^\sigma, \]
which displays how both the firm’s optimal export status decision and its scale of operation in the foreign market depends on its beliefs regarding export profitability.

### 3.3.2 Exporting and Self-Discovery

In this section I describe the self-discovery process of firms. The timing of events is as follows: at the beginning of the period the firm makes a quantity decision based on the information it has accumulated up to that point. After the firm makes its quantity decision demand uncertainty is realized (i.e. \( \theta_t \) is realized). The market clearing price for the firm’s output provides a signal that can be used by the firm to update its beliefs. That is, a firm’s revision of its export profitability depends on how realized revenues \( r_t \) compare to expected revenues \( r_t^e \):

\[ r_t - r_t^e = (h(\theta_t) - A_t) y_t^\frac{\sigma - 1}{\sigma}. \]

If a firm’s revenues at \( t \) are large compared to what it expected, it means that \( \theta_t \) was unusually high and this induces in an upward revision of “export profitability”. Notice that today’s high revenues are transformed into growth as firms use this newly acquired information next period to increase their scale of operation in the foreign market.

Firms use these signals to update their beliefs in a Bayesian manner. Notice, crucially, that the signals \( \theta_t \) are revealed only after the firm has made the decision equation
\[ U_t = \left[ (1 - \beta) c_t^\rho + \beta \left( \left[ E_t U_{t+1}^\alpha \right]^\frac{1}{\rho} \right)^{\frac{\rho}{\alpha}} \right]^{\frac{1}{1-\beta}}, \]
and \( \left[ E_t U_{t+1}^\alpha \right]^\frac{1}{\rho} \) represents the risk-adjusted continuation value.
to export. That is, exporting is a pure “experience good”. I could consider situations in which signals regarding export profitability are realized before the firm decides its export status. For example, exogenous signals, such as the export success of other exporters, could represent a secondary source of information regarding export profitability that is available to the firm before it decides whether to export or not (i.e. exporting could also be an “inspection good”, whose quality can be learned merely by inspecting it). However, as long as potential exporters cannot learn everything they need to know through these other external sources of information, there would still be a role for self-discovery through exporting. For the sake of simplicity here I abstract from such secondary sources of learning for the firm.

I study the firm’s signal extraction problem and Bayesian updating by utilizing the Kalman Filter. Let $z_t = \theta$, which I interpret as the hidden value of “export profitability”. Then, the firm’s learning problem can be posed in the state-space representation of the Kalman Filter:

\[
\begin{align*}
\text{(Evolution of Unobserved State)} & : z_{t+1} = z_t \\
\text{(Observation Equation)} & : \theta_t = z_t + \varepsilon_t; \varepsilon_t \sim i.i.d. \mathcal{N}(0, \nu_{\varepsilon}) \\
& \quad z_0 = \theta \sim \mathcal{N}(\mu_\theta, \nu_\theta),
\end{align*}
\]

where $\nu_{\varepsilon} = 1/\sigma_{\varepsilon}^2$ and $\nu_\theta = 1/\sigma_{\theta}^2$.

It will be convenient to define $\mu_t \equiv \mathbb{E}[\theta|\theta^{t-1}]$ and $\sigma_t^2 = \mathbb{E}[(\theta - \mu_t)^2|\theta^{t-1}]$, which capture the firm’s current beliefs about its true “export profitability” $\theta$. Then, the Kalman Filter implies that $\mu_t$ and $\nu_t = 1/\sigma_t^2$ evolve according to a controlled first-order Markov process, with transition equations for the mean and precision given

\cite{DeGroot1970} and Ljungqvist and Sargent [2012] provide a comprehensive discussion of the theoretical relationship between Bayesian updating and the use of the Kalman filter as a device for signal extraction.
by

\[ \mu_{t+1} = \mu_t + d_t \left( \frac{\nu_\varepsilon}{\nu_t + \nu_\varepsilon} \right) (\theta_t - \mu_t) \]

\[ \nu_{t+1} = \nu_t + d_t \nu_\varepsilon \]

\[ \mu_0 = \mu_\theta, \quad \nu_0 = \nu_\theta \text{ given.} \]

Additionally, the Kalman Filter implies the following conditional distributions

\[ \mu_{t+1} | \theta^{t-1} \sim \mathcal{N} \left( \mu_t, \frac{\nu_\varepsilon}{\nu_t (\nu_t + \nu_\varepsilon)} \right) \]

\[ \theta_t | \theta^{t-1} \sim \mathcal{N} \left( \mu_t, \frac{1}{\nu_t + \frac{1}{\nu_\varepsilon}} \right). \]

The firm’s level of uncertainty, as captured by the precision \( \nu_t \), evolves independently of the realization of signals: it only depends on the fact that a signal was received. This will offer a key simplification to the solution of the firm’s dynamic optimization problem. On the other hand, the evolution of the prior mean \( \mu_t \) will depend on the realization of signals since the new information revealed through observation of the signal, \( (\theta_t - \mu_t) \), will determine the direction in which the firm updates its beliefs regarding the mean of “export profitability”.

The pair \((\mu, \nu)\) are sufficient statistics for the firm’s information (i.e. beliefs regarding export profitability). Since \( \nu_t \) evolves deterministically, the transition equation for \( \nu \) readily implies that

\[ \nu_t = \nu_0 + n_t \nu_\varepsilon \quad \forall t \geq 0, \]

where \( n_t = \sum_{t=0}^{t-1} d_t \) is equal to the total number of periods on which the firm has decided to export before period \( t \). That is, tenure in the export market is a sufficient statistic for the precision of the firm’s beliefs regarding its export profitability.
Because I am interested in the relationship between export tenure, growth and survival as new exporters enter and exit from the foreign market, it proves useful to replace \( \nu_t \) with \( n_t \), the firm’s “export tenure”, as a state variable, with \( n \) evolving according to \( n_{t+1} = n_t + d_t \). This implies that the risk adjusted value of \( h(\theta_t) \) is a function of \((\mu, n)\) alone: \( A_t = A(\mu_t, n_t) \). Therefore, I may write the (expected) export profits as \( \pi(d, \mu, n) = d\pi(\mu, n) \), where

\[
\tilde{\pi}(\mu, n) = \left( \frac{1}{\sigma} \left( \frac{\sigma - 1}{\sigma} \right)^{\sigma-1} [A(\mu, n)]^\sigma - f_x \right).
\]

With \( h(\cdot) \) bounded, \( A(\cdot, \cdot) \) is also bounded and so are per period (expected) export profits \( \tilde{\pi}(\mu, n) \) for any \((\mu, n) \in \mathbb{R} \times \mathbb{R}_+ \).

Per-period expected export profits are non-decreasing in \( \mu \) and non-increasing in \( n \). To see why, other things equal, expected export profits are non-increasing with export tenure consider two firms \( i \) and \( j \) with the same beliefs regarding mean profitability \( \mu_i = \mu_j \), but with different tenures \( n_i \neq n_j \). Suppose that \( n_i > n_j \), then the conditional distribution for \( \theta_t \) for both firms is centered about the same value, but the firm with a longer export tenure has more precise information and thus its distribution is more compressed about the common mean. With a more compressed distribution, higher values for \( h(\theta_t) \) are assessed as less likely by the firm, which results in calculating a lower risk-adjusted value for \( h(\theta_t) \). This in turn leads to a lower optimal scale of operation, which results in lower expected export profits: \( \tilde{\pi}(\mu, n_i) \leq \tilde{\pi}(\mu, n_j) \).

Firm uncertainty regarding export profitability means that past experience in the export market will affect a firm’s information set, which in turn will affect their current choices. The dependence of information sets on export tenure will generate state dependence. The state dependence generated through the process of self-discovery gives the model an interesting dynamic component with firms adjusting their presence...
in the foreign market gradually as information comes in and in which export tenure is an important determinant of firm growth in the foreign market.

3.3.3 The Export Market Participation Rule: Firm’s Dynamic Optimization Problem

Firms will optimally choose to serve the export market depending on: (a) their beliefs regarding their export profitability, and (b) the fixed costs associated with maintaining a presence in foreign markets. Absent any additional sources of uncertainty the firm’s problem would be an optimal stopping problem: given current state variables, if the firm decided to stop exporting it would never re-enter the export market. The stopping property results from the fact that, without any additional sources of uncertainty, there is no reason for the firm to re-enter the foreign market once it has decided to exit.\(^\text{15}\)

In the data firms are constantly observed to be coming in and out of exporting. To address the model’s capability to rationalize the entry-exit behavior of exporters observed in the data, I assume that fixed costs of exporting at time \(t\) are given by

\[
f_{xt} = f_x + \zeta \epsilon_t,
\]

where \(\zeta > 0\), and where \(f_x\) denotes the observable component of fixed costs and \(\epsilon_t = \epsilon_{1t} - \epsilon_{0t}\) denotes unobserved (by the econometrician) state variables that may affect the decision to export. These fixed costs of serving the foreign market are faced every year and are independent of previous exporting history. I assume that \(\epsilon_{ti}\) are i.i.d. Extreme Value with shape parameter \(\gamma\) equal to the Euler-Mascheroni constant (this implies \(E[\epsilon_{ti}] = 0\), and independent of the other state variables \((\mu_t, n_t)\). The distribution of \(\epsilon_t\) is approximately Normal, but modeling this unobserved state variable as the

\(^\text{15}\)Unless there was a secular change in the fundamentals of the foreign market that would change the profitability of exporting, such as changes in market size or trade costs.
difference of Extreme Value distributions offers important computational advantages in terms of solving the firm’s dynamic optimization problem.

Prior to making the export decision, firms observe the current realization of \( \epsilon_t \). Thus, the firm’s state vector is given by \( s_t = (\mu_t, n_t, \epsilon_t) \). Let \( \vartheta \) denote the vector of parameters of the model. The dynamic programming problem characterizing the firm’s optimal export participation choice is given by

\[
V_{\vartheta}(\mu, n, \epsilon) = \max_{d \in D} \left\{ d \left( \pi(\mu, n; \vartheta) + \zeta \epsilon \right) + \beta \mathbb{E} \left[ V_{\vartheta}(\mu', n', \epsilon') | \mu, n, d \right] \right\},
\]

subject to the constraints on the evolution of the state variables given in section 3.2. Further details regarding the firm’s dynamic optimization problem can be found in the appendix.

Firms solve a dynamic program with discrete controls: the decision to export or not. Since firms are assumed to be forward-looking, firms make decisions today not only looking at current period payoffs, but also on the effect that choices today have on tomorrow’s information set. Recall that the focus here is on domestically established firms that have the potential to export, but have not yet done so, and their dynamics after export entry. Thus, by the way in which the firm’s value function \( V_{\vartheta} \) is defined it can be interpreted as the value to the firm of having the option to serve the foreign market.

It will be convenient to define

\[
W_0(n, \mu; \vartheta) \equiv \beta \mathbb{E} \left[ V_{\vartheta}(n', \mu', \epsilon') | n, \mu, d = 0 \right]
\]

\[
W_1(n, \mu; \vartheta) \equiv \tilde{\pi}(n, \mu; \vartheta) + \beta \mathbb{E} \left[ V_{\vartheta}(n', \mu', \epsilon') | n, \mu, d = 1 \right],
\]

which are commonly referred to as the “alternative specific” value functions in the discrete choice literature.

Then, I can write the firm’s dynamic optimization problem more compactly as
$V_\theta (n, \mu, \epsilon) = \max_{d \in D} \{ W_d (n, \mu; \vartheta) + \zeta \epsilon_d \}$.

I define the “exporter premia” as the difference between the alternative specific value functions: $\delta (n, \mu; \vartheta) \equiv W_1 (n, \mu; \vartheta) - W_0 (n, \mu; \vartheta)$. With this notation I can write the optimal policy rule for the firm as

$$d^*_t = d (n_t, \mu_t, \epsilon_t; \vartheta) = \mathbb{I} [\delta (n_t, \mu_t; \vartheta) + \zeta \epsilon_t > 0] ,$$

where $\mathbb{I} [\cdot]$ is an indicator function.

Using the definitions for $W_0$ and $W_1$, the exporter premia is given by

$$\delta (n, \mu; \vartheta) = \tilde{\pi} (n, \mu; \vartheta) + \beta [\mathbb{E} [V_\theta (n', \mu', \epsilon') | n, \mu, d = 1] - \mathbb{E} [V_\theta (n', \mu', \epsilon') | n, \mu, d = 0]].$$

This model based definition of the exporter premia differs from that commonly estimated in reduced form regressions. In particular, this definition of the exporter premia crucially includes the option value created for the firm from the advantage that additional information can have on deciding tomorrow’s optimal scale of operation in the foreign market and optimal export market participation decision. Thus, the premium to becoming an exporter is composed of two terms: (i) $\tilde{\pi} (n, \mu; \vartheta)$ the current period (expected) payoff from serving the foreign market; and (ii) the “gains from trial”:

$$G (n, \mu; \vartheta) \equiv \beta [\mathbb{E} [V_\theta (n', \mu', \epsilon') | n, \mu, d = 1] - \mathbb{E} [V_\theta (n', \mu', \epsilon') | n, \mu, d = 0]].$$

The “gains from trial” arise from the fact that by exporting the firm receives information that allows it to decrease the amount of uncertainty regarding export profitability. This option value arises from the forward-looking nature of the firm’s optimal export status decision and the state dependence that self-discovery induces in the firm’s
information set. This results in a key difference in relation to static models of export supply a la Melitz [2003]. The “gains from trial” are akin to the option value of exporting that arises in models with sunk entry costs (see, for example, Das et al. [2007]): by not exporting the firm forgoes a (possibly positive) stream of profits in the foreign market. However, by exporting today, even possibly at a loss, the firm acquires the option to not export tomorrow based on more precise information regarding the payoffs from serving the export market.

The “gains from trial” are approximately given by

\[ G(n, \mu; \vartheta) \approx W_0(n + 1, \mu; \vartheta) - W_0(n, \mu; \vartheta), \]

the change in the value of not exporting when this decision is made with more precise information regarding the firms true export profitability (see section 8 for details).

3.4 Estimation

In this section I describe the parametrization and estimation of the model outlined in section 3. The structural parameters are estimated using simulation methods. Within the estimation procedure, the dynamic programming problem defining the firm’s optimal policy rule is solved for each guess of the parameter vector. Using this parameter vector and corresponding policy rule, an artificial dataset is simulated from which moments are computed for a moment matching exercise. The following sections discuss these points in detail.

3.4.1 Parametrization

For the purposes of estimation I need to specify a functional form for the function \( h(\cdot) \). Here I assume that \( h \) takes the form \( h(z) = \kappa \exp(-\lambda \exp(-gz)) \), where \( \kappa > 0 \) and \( \lambda, g > 0 \). Under this functional form assumption:
1. \( h(z) \geq 0 \) for all \( z \geq 0 \).

2. \( h(\cdot) \) is continuous, differentiable, and monotone increasing.

3. \( h(\cdot) \) satisfies

\[
\lim_{z \to \infty} h(z) = \kappa \\
\lim_{z \to -\infty} h(z) = 0.
\]

This functional form assumption imposes the boundedness condition assumed in section 3, while allowing for flexibility in the shape that \( h(\cdot) \) can take on its domain.\(^{16}\)

The parameter \( \kappa \) controls the upper bound for \( h(\cdot) \), while \( \lambda \) and \( g \) affect the growth rate of \( h(\cdot) \). Observe that \( \kappa \) plays an interesting role: if \( \kappa \leq 1 \) then, for the same scale of operation, revenues in the foreign market are strictly lower than domestic revenues. On the other hand, if \( \kappa > 1 \) then, for the same scale of operation, the firm can (potentially) earn larger revenues in the export market than it can in the home market. In the model, the maximum foreign market revenues attainable for the firm are entirely determined by \( \kappa \) and \( \sigma \): \( r_{\text{max}} = \kappa^\sigma (((\sigma - 1)/\sigma)^{\sigma-1} \).\(^{17}\)

I assume that \( \beta \), the time discount factor, and \( \sigma \), the CES elasticity of substitution, are known and set \( \beta = 0.96 \) and \( \sigma = 5 \). This value for the time discount factor is standard in the literature and it is the one used by Alessandria et al. [2013]. The

\(^{16}\)Because this is a bounded, positive and monotone function, \( h(\cdot) \) must be “S-shaped” on this domain. However, the parameters \( \lambda \) and \( g \) provide flexibility in terms of the displacement along the \( x \)-axis and growth rate, respectively.

\(^{17}\)In the model, observed export revenues are given by \( r_t = h(\theta_t) y_t^{\frac{\sigma - 1}{\sigma}} \), where \( y_t^* \) is the optimal scale of operation. Given the assumed functional form assumption for \( h(\cdot) \), the risk-adjusted expected value of \( h \) is given by

\[
A_t = \left( \mathbb{E} [ (h(\theta_t))^\sigma | T] \right)^{\frac{1}{\sigma}} = \kappa \left( \mathbb{E} [ \exp (-\lambda \sigma \exp (-g \theta_t)) | T] \right)^{\frac{1}{\sigma}},
\]

where \( 0 \leq (\mathbb{E} [ \exp (-\lambda \sigma \exp (-g \theta_t)) | T] )^{\frac{1}{\sigma}} \leq 1 \). Thus, export revenues can be written as

\[
r_t = \kappa^\sigma \exp (-\lambda \exp (-g \theta_t)) \left( \frac{\sigma - 1}{\sigma} \right)^{\sigma-1} \mathbb{E} [ \exp (-\lambda \sigma \exp (-g \theta_t)) | T],
\]

which immediately implies the given upper bound for export sales.
choice for $\sigma$ draws on various sources. Alessandria et al. set $\sigma = 5$ to generate a 25% markup for firms; Broda and Weinstein report that for the period 1990-2001 the average elasticity of substitution was 8 for 10-digit (HTS) goods and 4 within 3-digit goods. Furthermore, Lai and Trefler [2002] report an estimated elasticity of substitution of approximately 5 for various econometric specifications considered by the authors. In particular, their maximum likelihood estimate of $\sigma$ is 5.25. Based on these disparate sources of evidence I set $\sigma = 5$.

### 3.4.2 Estimation Procedure

Since the model outlined in section 3 involves unobserved state variables, I estimate the remaining parameters $\theta = (\nu_x, \mu_\theta, \nu_\theta, f_x, \lambda, g, \kappa, \zeta)$ using indirect inference methods as discussed in Gouriéroux and Monfort [2002]. In particular, I use the moment-matching simulation estimator:

$$\hat{\theta} (\Omega) = \arg\min_{\theta} (\hat{m}_d - \hat{m} (\theta))^T \Omega (\hat{m}_d - \hat{m} (\theta)),$$

where $\hat{m}_d$ is a vector of data moments, $\hat{m} (\theta)$ are the corresponding simulated moments for parameter vector $\theta$, and $\Omega$ the weighting matrix defining a metric for the distance between the data and the simulated moments.  

The estimate $\hat{\theta}$ is the result of an iterative procedure: for an initial guess $\hat{\theta}_1$ I calculate the optimal weighting matrix $\hat{\Omega}_1$ and use this to calculate $\hat{\theta}_2 = \hat{\theta} (\hat{\Omega}_1)$. This process is repeated until the estimates for $\hat{\theta}_j$ converge, yielding the moment-matching

---

18I do not estimate the model via maximum likelihood because constructing the likelihood for this model imposes a greater computational burden than simulating moments. In particular, the probability of observing a particular export history $d = (d_1, \ldots, d_T)^T$, which is required to evaluate the likelihood, must be constructed by integration over all histories $\mu$ that are consistent with $d$ since $\{\mu_t\}_{t=1}^T$ is an unobserved state variable. This high-dimensional integral does not have a closed form solution and must be approximated by simulation. These high dimensional integrals have to be approximated for all unique export histories that are observed in the data. Doing so to evaluate the likelihood increases the computational burden relative to the moment matching approach taken here.
simulation estimator \( \hat{\vartheta} \). Details of the estimation procedure can be found in the appendix.

### 3.4.3 Specifying Moments

For a candidate value \( \vartheta \), I simulate the export sales and dynamics of 20,000 firms using the model outlined in section 3. Out of these 20,000 firms I choose the subset of firms that exported in the initial period and track the outcomes of these firms over time in analogy to the cohort of exporters analyzed in section 2. In the data, the 2001 cohort of Mexican exporters is comprised of approximately 13,000 firms.\(^{19}\) By simulating 20,000 firms I obtain new exporting cohorts of roughly the same size as those seen in the data. For the artificial data I compute a vector of moments \( \hat{m}(\vartheta) \) analogous to particular moments \( \hat{m}_d \) in the data. The set of moments that I use for estimation are:

1. Mean log Sales (conditional on exporting) for the first three period of the cohort.\(^{20}\)

2. Continuations rates for \( n = 0, 1, \ldots, 5 \), where \( n \) denotes years since export entry.

3. Average export tenure.

In total I use 10 moments to identify 8 parameters. The first-year mean log sales will contain information about the initial scale of operation of firms, and thus about the initial beliefs regarding export profitability \( \mu_\theta \) and \( \nu_\theta \). Together, the set of moments concerning mean log sales will also provide information relating to the revenue function parameters \( \kappa, \lambda, \) and \( g \). The continuation rates and average export tenure will provide information about the entry-exit behavior of firms that will be

---

\(^{19}\)Exporting cohorts for 2002-2007 are of a similar size.

\(^{20}\)Due to partial year effects (see Bernard et al. [2014]), I make an adjustment to the data moment corresponding to the first year mean log sales by assuming that export entrants and their revenues are uniformly distributed over the calendar year.
informative about the parameters that affect the optimal export status decision of firms such as the fixed costs \( f_x \), the rate of learning \( \nu_e \), and the size of the idiosyncratic shocks to fixed costs \( \zeta \).

### 3.4.4 Estimation Results and In-Sample Model Performance

The best fit is achieved at the parameter values reported in Table 3.1 below. Table 3.2 reports the data moments used in estimation and their counterparts in the model for the estimated parameter values. Compared to the data, in the model firms live (on average) for slightly longer and start out smaller. The fact that firms start smaller in the model but in their second year reach export sales similar to those observed in the data means that the model will over-predict the first year average growth rate of firms (conditional on survival).

In order to generate the large attrition rate of firms after the first year that is observed in the data the model needs to generate a large mass of firms with relatively low export sales (which is the signal that would tell firms that they are unprofitable exporters) that drags down the mean export sales of the first year in the model. In simulation exercises, attempts to push these two simulated moments closer to their empirical counterparts resulted in a higher discrepancy between the data and simulated moments for second and third year mean log sales. The first-year continuation rate and the first year mean log sales cannot be simultaneously pushed closer to their data counterparts without affecting the value of other matched moments because all parameters jointly determine all moments.
Table 3.2: Matched Moments

Figures 3.4.1 serves as a check for over-identification as it compare the predictions of the estimated model for some non-targeted data moments. Figure 3.4.1 presents the distribution of export tenures (no. of years as an exporter). The model does a good job matching the tail of this distribution: for 4 or more years as an exporter the data and model frequencies are a good match. However, the model implies that after the large attrition rate of the first year firms are subsequently more likely to re-enter the export market than what is observed in the data. This implies that the model over-predicts the likelihood of 2 and 3 year tenures and under-predicts the likelihood of single-year exporters. That is, in the model, even after receiving a very bad signal about export profitability in the initial period, firms are likely to re-enter the export market after receiving a good enough idiosyncratic shock to their fixed costs of serving the foreign market.

Figure 3.4.2 graphically depicts the continuation rates presented in Table 3.2 to more clearly show that the estimated model is able to provide a good fit to continuation rates that are increasing with export tenure as observed in the data. Figure 3.4.3 presents the growth dynamics of “long-term” survivors. As mentioned
above, the large first year attrition rate is generated by the model at the cost of relatively low (average) first year export sales, which results in over-predicting the first-year growth rate. This stands in contrast to models of exporter dynamics based on financial frictions such as Leibovici et al. [2015] where first-year growth rates are under-predicted. However, the model with self-discovery does generate the growth dynamics observed in the data: very strong average sales growth in the first year, followed by rapidly decaying growth rates.\footnote{In the midpoint of the sample, 2004, there appears to be a generalized increase in all export activity from Mexican exporters (see Cebreros [2014]). Exports as a share of GDP averaged 24.5% between 2001 and 2004, and increased to an average of 27.6% between 2005 and 2009. This increase in the share of exports in GDP coincides with a 7% reduction in the weighted average tariff index for industrial production and an elimination of effectively applied tariffs with Canada and a gradual elimination of these same tariffs with the USA, Mexico’s two largest trading partners (see the World Bank’s World Integrated Trade Solution http://wits.worldbank.org/default.aspx). This suggests that the growth dynamics of long-term survivors observed in the data decayed more slowly than they otherwise would have as firms adjusted to this trade liberalization. Additionally, in the data there is a large drop in export sales towards the end of the sample due to the 2007 financial crisis.}

The evidence presented here shows that the estimated model gives rise to entry-exit behavior and growth that is consistent with the data. In particular, Figures 3.4.2 and 3.4.3 show that the model with self-discovery can \textit{qualitatively} and \textit{quantitatively} succeed in explaining the gradual adjustment of new exporters observed in
Figure 3.3: Exporter Continuation Rate: Conditional Survival Probabilities

Figure 3.4: Growth Dynamics of Long-Term Survivors
the data, a feat not achieved by the standard sunk entry cost model with productivity heterogeneity (see Ruhl and Willis [2014]).

3.5 Implications of Self-Discovery for Export Supply: Profits, Option Values, and the Effects of Tenure

In this section I use the parameter estimates of section 4 to calculate option values, probabilities, and scales of operation. These objects will be useful to understand the dynamic adjustment of export supply as firms transition from new to mature exporters. In particular, I will be interested in quantifying the role that self-discovery plays in the export supply decisions of new exporters and the length of time in the export market necessary for firms to uncover their true export profitability.

3.5.1 Option Values: Quantifying the Gains from Trial

In section 3 it was argued that the “gains from trial” represent a crucial component of the exporter premia that shapes the export supply decision of firms. I use the estimated model to quantify the importance of this option value for the dynamics of new exporters and to show how the dynamic model differs from a static model of export supply.

To gain further insights into how the exporter premia and the “gains from trial” evolve as a cohort of new exporters matures I will define the “term structure” of the “gains from trial”, conditional on survival. Let \( \delta_t \) and \( G_t \) be the average export premia and average gains from trial, where the average is taken over the set of firms that export in both \( t \) and \( t + 1 \) (i.e. the “continuers”). Figure 3.5.1 presents the evolution
of the share of the “gains from trial” $G_t$ in the exporter premia $\delta_t$:

$$s_{G_t} = \frac{G_t}{G_t + \delta_t}.$$

If $s_{G_t} > 1$, then the export premia $\delta_t$ is negative and since $G_t$ is non-negative this implies that expected export profits must be negative. Similarly to Alessandria et al. [2013], I find that new exporters will, on average, earn negative profits on entry. For first time exporters the value they attach to the information gained through serving the export market is the most important component to the value from serving the foreign market. With no previous export experience, the “gains from trial” compensate new entrants for their expected losses to the point of leaving them indifferent between entering the export market or not. Entry of new exporters is driven by temporary below average fixed costs of entering the export market.

Figure 3.5.1 shows that the initial export period provides a crucial learning experience for first-time exporters and that following the initial participation in the foreign market there there is a very quick and sharp drop in the contribution of the “gains from trial” in the exporter premia. However, Figure 3.5.1 also shows that there is a positive value to learning over the first four years of the firm’s tenure in the export market. That is, export profitability is not entirely uncovered by the firm in its first year serving the export market. It is only after the discovery stage that the export premia is entirely comprised of expected export profits and learning about the foreign market ceases to have any value for the firm.

To further understand the role of the gains from trial in shaping the export supply decision of firms it is also interesting to understand how the forward-looking behavior of firms affects entry-exit decisions. To do so I simulate a myopic version of the model ($\beta = 0$) and compare this to the forward-looking model ($\beta > 0$). Myopic firms will learn their export profitability in the same way that forward-looking firms do, the
only difference is that the export supply decision of myopic firms is entirely shaped by the expected profits in the foreign market. That is, when making export supply decisions myopic firms do not place any value on how serving the foreign market can affect their information sets. Figure 3.5.2 depicts the difference in continuation values between the forward-looking and myopic models. We can see that in the first three years of tenure in the export market the “gains from trial” has a non negligible effect on the export supply decision of firms, resulting in higher continuation rates for forward-looking firms relative to their myopic counterparts. After this discovery stage, the difference in continuation rates is negligible or non-existing since firms have mostly uncovered their true export profitability and thus the gains from trial play an inconsequential role in determining the firm’s export supply decision.

### 3.5.2 The Effects of Tenure on Export Status

How does the probability of serving the foreign market change with export tenure? In section 3 it was shown that tenure is a sufficient statistic for the precision of the firm’s information. Here I quantify how tenure affects the decision to serve the export market. Given the distributional assumptions of section 3, the ex-ante probability of
exporting\textsuperscript{22} given state variables \((\mu, n)\) is given by

\[
Pr (d = 1|\mu, n) = \left( 1 + \exp \left( - \frac{\delta(\mu, n; \hat{\vartheta})}{\zeta} \right) \right)^{-1}.
\]

Since this probability depends on the unobserved state variable \(\mu\), I define

\[
P_t := \left( 1 + \exp \left( - \frac{\tilde{\delta}_t}{\zeta} \right) \right)^{-1},
\]

where \(\tilde{\delta}_t := H_t^{-1} \sum_{h=1}^{H_t} \delta \left(n_t^h, \mu_t^h, \hat{\vartheta} \right)\). Here \(H_t\) denotes the number of firms that have exported every period through \(t - 1\) (i.e. conditional on survival, \(H_t\) is the set of potential exporters in period \(t\)).

Table 3.3 presents the effects of tenure on the probability of being an exporter. The first row shows how this probability evolves, while the second row shows the evolution of this probability relative to the probability of serving the foreign market for a firm with no previous experience in the export market. To better understand these results, the third row of Table 3.3 shows the evolution in the (average) export

\textsuperscript{22}By ex-ante probability of exporting I mean the probability of serving the foreign market before the firm observes the idiosyncratic shock to its fixed export costs.
premia of potential exporters. Changes in these rewards to exporting are the driving force behind changes in the likelihood of serving the foreign market. The first thing that can be gleaned from Table 3.3 is that after the first year there is a large drop in the likelihood of serving the export market. The reason behind this result is a powerful selection effect that affects first-time exporters. Recall that $H_t$ is the set of, conditional on survival, potential exporters at time $t$. By definition of the exporting cohort and of $H_t$, the set of exporters in $t = 0$ and of potential exporters at $t = 1$ is the same. The initial exporting period reveals a lot of information to export entrants, and during their first venture into the export market many members of the initial cohort of exporters will receive unfavorable information regarding their export profitability. The third row of Table 3.3 demonstrates how the revelation of unfavorable information regarding export profitability that drives the high first-year exit rate entails a drop in the average exporter premia for the set of potential second-year exporters. After the sharp attrition rate that occurs during the first year, this selection is dominated by the increase in the export premia of continuing firms and we observe that the exporter premia of the average potential exporter gradually increases giving rise to a positive, but diminishing, effect of tenure on the probability of being an exporter.

After a firm has maintained a continuous export presence for 7 years, the (ex-ante) probability that it will serve the foreign market in the current period increases by 137%. During this same time span, “long-term” survivors see their export premia grow by approximately 900% as they develop from new to established exporters. Conditional on survival, the increase in the ex-ante probability of serving the foreign market is concentrated in the first four years of tenure: after the 4th year the ex-ante

<table>
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<th>$t = 1$</th>
<th>$t = 2$</th>
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<td>2.34</td>
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<td>-0.01</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.04</td>
<td>0.06</td>
<td>0.07</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Table 3.3: Effect of Tenure on the (ex-ante) Probability of Exporting
probability of serving the foreign market has already experienced 95% of its long-term adjustment. These numbers reveal that valuable rewards are available to those firms lucky enough to discover that they can profitably serve the foreign market.

The model of export supply with self-discovery leads to a theory of “noisy” selection in which exporters, through a bit of luck, are able to gradually learn their true export profitability. This process of noisy selection can account for the gradual thinning of active firms in the export market that is observed in the data, and continuation rates that are increasing with export tenure. To further understand how tenure and selection work in the model, I define “export cutoff” $\mu^* = \mu(n)$ by

$$\mu(n) = \inf \left\{ \mu : \delta(\mu, n; \hat{\theta}) > 0 \right\}.$$  

Figure 3.5.3 plots the evolution of the cutoff for export entry $\mu^*$. In contrast to the static model of Melitz [2003], where the cutoff for export entry is fixed and only responds to changes in fixed costs and/or changes in the distribution of production heterogeneity, here the cutoff for export entry changes with tenure. At any finite $t$, the threshold for exporting is more lax than the zero-profit cutoff “at infinity”. As was discussed in section 5.1, early in the firm’s tenure the entry decision is mostly driven by the gains from trial so firms are willing to export even at an expected loss because of the value they attach to gathering information. As information comes in which allows exporters to decrease the amount of uncertainty regarding their true profitability in the export market, firms are able to set export cutoffs more accurately.

The cutoffs for export entry converge from below to the zero-profit cutoff “at infinity” as the value to gathering information decreases over time. Notice, specially, that after the initial year there is a substantial adjustment in the cutoff for export entry. This sharp increase increase in the cutoff for export entry after the initial year

\[\text{The zero-profit cutoff “at infinity” is the cutoff for export entry once firms have learned their true export profitability, which is equivalent to the zero-profit cutoff in the static Melitz model.}\]
accounts for the large attrition rate of first-time exporters. Figure 3.5.3 also shows that not all adjustment occurs after the first period: export cutoffs continue to adjust after the first year of tenure in the export market, with 90 percent of the adjustment occurring in the first four years of tenure in the foreign market.

3.5.3 Implications for the Intensive Margin

Turning to the adjustment of the foreign market presence of new exporters, results presented in chapter 2 showed that the deepening of export relationships is key in understanding the export growth of new exporters. In particular, the firm’s intensive margin was shown to be a key channel through which long-term survivors expand their foreign market presence as they mature into well established exporters. I use the estimated model to investigate how self-discovery affects the adjustment of the firm’s optimal scale of operation in the foreign market.

In section 3 it was shown that the firm’s optimal scale of operation in the foreign market was given by

$$y^*_t = \left(\frac{\sigma - 1}{\sigma}\right) A_t^\sigma,$$
where $A_t$ was the risk-adjusted expected value of $h(\theta_t)$. Here I write $A^*_t = I(\mu_t, n_t; \hat{\vartheta})$, and decompose the adjustment in the firm’s scale of operation into the effect of receiving more (less) favorable information and the effect of obtaining more precise information as

$$\log y^*_{i,t+1} - \log y^*_{i,t} = \log I(\mu^i_{t+1}, n^i_{t+1}; \hat{\vartheta}) - \log I(\mu^i_t, n^i_t; \hat{\vartheta}) = \underbrace{\log I(\mu^i_{t+1}, n^i_{t+1}; \hat{\vartheta}) - \log I(\mu^i_t, n^i_t; \hat{\vartheta})}_{\text{effect of change in beliefs regarding mean export profitability}} + \underbrace{\log I(\mu^i_t, n^i_{t+1}; \hat{\vartheta}) - \log I(\mu^i_t, n^i_t; \hat{\vartheta})}_{\text{effect of more precise information}}.$$

Table 3.4 presents the results of this decomposition for the set of long-term survivors. The first column presents the (average) growth in the intensive margin, while columns two and three decompose this growth into the effect of a change in the beliefs about mean export profitability and the effects of more precise information, respectively.

The first three years are particularly meaningful since mean log sales for the first three years of the cohort were part of the targeted moments used for estimation in Section 4. Table 3.4 shows that the growth in the foreign market presence of long-term survivors is driven by the effect of the change in beliefs regarding the mean of export profitability: positive information regarding export profitability translates into growth as newly acquired information is used to adjust the optimal scale of operation in the foreign market.

On the other hand, Table 3.4 reports that the effect of more precise information is to contract the firm’s foreign market presence. From section 3 we know that, conditional on the firm’s information set, the distribution for the revenue shock faced by the firm is given by

$$\theta_t | \mathcal{F}_t \sim \mathcal{N}\left(\mu_t, \frac{1}{\nu_\theta + n_t \nu_\varepsilon} + \frac{1}{\nu_\varepsilon}\right).$$
| t + 1 | 179.00 | 499.36 | -320.36 |
| t + 2 | 16.53  | 17.41  | -0.88   |
| t + 3 | 3.79   | 3.84   | -0.05   |
| t + 4 | 0.90   | 1.22   | -0.32   |
| t + 5 | 0.05   | 0.42   | -0.37   |
| t + 6 | -0.04  | 0.26   | -0.30   |

Table 3.4: Decomposing the Intensive Margin of Firm Adjustment: Long-Term Survivors

Thus, when the firm receives information that does not lead to a change in its beliefs regarding mean export profitability, the only effect of this additional information is to compress the conditional distribution of $\theta_t$ about its current mean. This compression implies, in particular, that the firm perceives a decreased likelihood for very high values of the demand shifter that in turn results in a downsizing of the firm’s scale of operation in the foreign market. The results in Table 3.4 also show that, conditional on survival, the first-year of tenure in the export market reveals a large amount of information to firms that results in high first-year growth rates for continuing firms. Table 3.4 also shows that during the first four years of tenure in the export market there are non-negligible adjustments along the intensive margin: full adjustment in the firm’s foreign market presence is not attained immediately after surviving the first period.

To summarize, I have shown that: (i) first-time exporters expect to incur losses by serving the foreign market; the option value generated by the acquisition of more precise information regarding export profitability compensates inexperienced exporters for their losses and entry is driven by below average costs of serving the foreign market; (ii) the “gains from trial” as a share of the export premium remains positive for the first four years of tenure in the export market, after this initial discovery stage the export premia is entirely comprise of expected export profits; (iii) long-term survivors observe a 137% increase in their ex ante probability of serving
the foreign market and a 900% increase in their (average) export premia as they transition from new to mature exporters; 95% of the long-term adjustment in the ex ante probability of being an exporter is attained during the first four years of tenure in the export market; (iv) self-discovery leads to a theory of noisy selection with the cutoff for serving the foreign market converging from below to that static full-information export cutoff; 90% of the adjustment in the cutoff for exporting is realized in the first four years of export tenure, and (v) the growth in the foreign market presence of long-term survivors is led by growth in the intensive margin, where most growth occurs after the initial revelation of information regarding export profitability. However, full adjustment is not attained after surviving the first year, adjustments along the intensive margin continues during the first four years of tenure in the export market. More precise information regarding export profitability leads to a downsizing in the scale of operation of firms. Positive growth for long-term survivors is the result of above expected performance in the export market, which is a source of positive information regarding the mean of export profitability.

Using the estimated model I find that, while the first year of tenure in the export market provides a crucial learning experience for firms, export profitability is not uncovered after the first year serving the foreign market. The results of this section suggest that the discovery stage last approximately four years. This result contrasts with the reduced formed evidence presented by Albornoz et al. [2012], who find that uncovering export profitability is attained in the firm’s first year as an exporter. The fact that export profitability is not fully uncovered in the first year implies that, conditional on survival, firm’s will not fully adjust their foreign market presence immediately. Adjustment continues for a number of periods as firms gradually uncover export profitability, and it is this gradual learning that leads to the firm dynamics that is observed in the data concerning growth and survival of new exporters.
3.6 Counterfactual Analysis: The Speed of Learning, Export Promotion and Implication for Aggregate Trade

In section 3 it was shown that the firm’s signal extraction problem and Bayesian updating implies that the precision of the firm’s beliefs regarding its unknown export profitability evolve as

$$\nu_{t+1} = \nu_t + d_t \nu_\varepsilon$$

where $\nu_\varepsilon$ is the precision of the revenue (demand) shocks faced by firms in the foreign market. The rate at which firms increase the precision of their information (i.e. the speed of learning) is entirely determined by the parameter $\nu_\varepsilon$: the more variability there is in the demand shocks faced by the firm, the less information it can extract from its signals.

Firms may face different learning environments if, for example, learning is destination and/or industry specific. On this latter point it is often argued that entrant firms may differ significantly on product characteristics and that producers of customized products are involved in more extended learning processes than are producers of standardized products (see Pedersen and Petersen [2003]). Waller et al. [2001] document that demand variability ranges widely across product categories/industries: basic consumer products exhibit low demand variability, while more differentiated products such as electronics exhibit significantly higher demand variabilities due to their short product life cycles. In the context of the present model, these differences in demand variability across industries can be interpreted as differences in the parameter $\nu_\varepsilon$ and thus, as differences in the learning environment faced by firms in different industries.
In this section, I study the export supply consequences of the learning environment faced by firms by considering a counterfactual environment where learning happens more slowly by reducing $\nu_e$ to 25% of its benchmark value. Figure 3.6.1 shows the evolution of the gains from trial as a share of the exporter premia for both the benchmark and slow learning case. As might be anticipated, in the slow learning environment the value that firms attach to the option value of making future choice using more precise information is greater as reflected by the higher participation of the gains from trial in the exporter premia. It can also be seen that the value of learning remains positive for approximately 50% longer in the slow learning environment relative to the benchmark. This speaks to the point mentioned above that producers of customized products (where demand is more volatile) undergo learning processes that are more prolonged than those experienced by producers of standardized products.

Figures 3.6.2 present the effect of a slower learning environment on continuation rates. As might be expected, when it takes more time for firms to uncover their export profitability they are less likely to continue serving the export market. Figure 3.6.2 shows that in the slow learning environment continuation rates are uniformly lower than in the benchmark case: even when firms receive a very positive signal $\theta_t$, the
amount of information they are able to extract about \( \theta \), their “fundamental export profitability”, is small since the signal contains a lot of noise. Thus, firm’s beliefs regarding their export profitability adjust slowly, which results in less firms deciding to continue serving the export market.

Evidence presented by Sabuhoro et al. [2006] for Canadian exporters shows that exporters in service providing industries such are business services, construction, and finance (which are more customized) are more likely to exit export markets than firms in good providing industries such as fishing and trapping and logging and forestry (which are more standardized). This pattern of results is consistent with the findings shown in Figure 3.6.2.

Sectoral differences in continuation rates can be accounted for by the learning model of section 3 if demand volatility varies by sector since this would imply that producers in different sectors face different learning environments. Also, exporter continuation rates that differ across destinations, as documented by Besedes and Prusa [2011], can be accounted for by the learning model if demand volatility varies across destinations.
3.6.1 Export Promotion and Aggregate Trade

Over the last two decades national export promotion agencies (EPAs) have tripled and have had a strong and statistically significant impact on aggregate export volumes (see Ledermand et al. [2010]). The case for export promotion is, however, contentious (see Grossman [1998]). Nevertheless, given the popularity of export promotion policies in developing nations and the prominence given to these by policymakers as an integral part of a nation’s development strategy (see Bhagwati [1988]) it is of interest to investigate the impact of these policies on export volumes. Here the focus is not normative, it is merely a positive evaluation of the type of export promotion policies typically carried out by policymakers and EPA’s (see, for example, OECD [2009]). The objective is as in Roberts and Tybout [1997] and Das et al. [2007]: to understand how micro-founded firm level export dynamics affect aggregate exports in response to changes in the economic environment that effect the profitability of serving the foreign market.24

The type of export promotion policy I consider here are direct subsidies to the fixed costs associated with maintaining a foreign market presence.25 Policy makers justify these type of export assistance programs under the guise that there are exporting firms that would increase their foreign market presence and non-exporters that would start to export, but do not do so because they lack crucial information about foreign markets (see Pursell [2000]). In the current setup, export promotion policies would

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24Roberts and Tybout (1997) write “Export supply responsiveness is of central concern to the World Bank and its client countries. The success of structural programs has depended significantly on the extent to which strong export responses have followed commercial policy reforms and devaluation...Strong export responses have also enabled countries to quickly reap the efficiency gains associated with larger trade volumes. Unfortunately, export supply responses are not well understood...Seemingly similar reform packages have generated a large range of export responses in different countries and time periods. Policymakers have faced substantial uncertainty whether a given reform package will, for their country, generate the needed response.”

25For example, in Australia the Export Market Development Grants scheme reimburses up to 50% of eligible export promotion expenses that are above a given threshold.
help firms overcome the key piece of information they are missing: knowledge about persistent demand components in the foreign market.

I simulate the effects of a temporary export subsidy to the fixed costs of exporting of 50, 75 and 100 percent of the benchmark value. From the date at which the EPA makes the subsidy available it lasts for three years (i.e. if the EPA announces the subsidy program at \( t \) the subsidy is available until \( t + 2 \)). I also consider the impact of these trade policies in a counterfactually slow learning environment.

As can be seen from Figure 3.6.3, temporary export subsidies can have permanent consequences on aggregate trade. The temporarily low cost of serving the export market implies that some unprofitable exporters will remain in the export market longer than they should, but it also means that profitable exporters who are unlucky at the outset of their export tenure can remain in the export market long enough to uncover that they can profitably serve the export market. It is precisely these firms that account for the long term increase in trade volumes in response to temporary subsidies.

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A 100 percent subsidy implies that the EPA completely funds the fixed cost of serving the foreign market.
Figure 3.11: The Impact of the Speed of Learning on Export Promotion

Figure 3.6.3 shows the effects of the speed of learning on the impact of export promotion. The simulation results presented in figure 3.6.4 suggest that in the long-run there are no consequences for aggregate trade volumes: in response to a temporary subsidy to the fixed costs of exporting, aggregate trade volumes converge to the same value regardless of the speed of learning. As is clear from this figure, it is during the transition that the speed of learning can affect the influence of export promotion. Over a 15 year horizon, the net present value of the trade that is “lost” under the counterfactually slower learning environment is in the order of 13.6 billion U.S. dollars for a policy that temporarily subsidizes 75% of the fixed costs of exporting.\textsuperscript{27} Thus, the effectiveness of temporary export subsidies, in terms of engineering aggregate trade growth, is critically affected by the speed at which firms are able to learn their way out of the uncertainty they face in the foreign market.

\textsuperscript{27}I use the same discount factor used by firms in section 3, which is equivalent to discounting at a 4% annual real rate of interest.
3.7 Conclusions

In this chapter I have developed and estimated a quantitative model of export dynamics featuring self-discovery. The estimated model accounts well for the pattern of export dynamics of new exporters that is observed in the data. In particular, the model is able to qualitatively and quantitatively account for the relationship between growth, survival, and tenure in the export market that is observed in the data: (a) continuation rates that are increasing with export tenure, and (b) high initial and subsequent gradual growth of export sales of new exporters.

The model provides a framework that can be used to quantify the role of learning dynamics in shaping the firm level export decision. Additionally, the model can be used to undertake counterfactuals for the effects of trade liberalization on micro and macro export growth. The main results that I obtain from the estimated model and counterfactuals are: (i) first-time exporters expect to incur losses by serving the foreign market; the option value generated by the acquisition of more precise information regarding export profitability compensates inexperienced exporters for their losses and entry is driven by below average costs of serving the foreign market; (ii) while the first-year serving the foreign market provides a crucial learning experience for new exporters, the discovery stage is more prolonged: the value of learning remains positive for the first four years of tenure in the export market. During the discovery stage, the export cutoff experiences 90% of its long-term adjustment and the (ex-ante) probability of serving the foreign market for long-term survivors realizes 95% of its long-term adjustment; (iii) in the transition from new to established exporters, long-term survivors observe a 137% increase in their ex-ante probability of serving the foreign market and a 900% increase in their (average) export premia, and (iv) temporary shocks to the profitability of serving the export market can have permanent consequences on aggregate trade volumes. In particular, export promotion policies that temporarily subsidize the fixed costs of maintaining a presence in the foreign
market can result in permanent increases in aggregate trade volumes. However, the impact of these types of policies crucially depends on the speed at which firms are able to uncover their export profitability.

In contrast to the evidence on learning and export dynamics afforded by reduced form specifications such as those considered by Albornoz et al. [2012], by developing and estimating a structural model of export supply featuring self-discovery I was able to quantify the role of learning in shaping the export supply decision of firms. By doing so I found that export profitability is not fully uncovered in the first year as suggested by these authors: the discovery stage lasts for approximately four years. Conditional on survival, firm’s will not fully adjust their foreign market presence immediately. Adjustment continues for a number of periods as firms gradually uncover export profitability, and it is this gradual learning that leads to the firm level export dynamics that is observed in the data concerning the growth and survival of new exporters.

In order to highlight the role that self-discovery plays in explaining the relationship between export tenure, growth and survival, the model has abstracted from certain aspects that are important in shaping the internationalization process of new exporters. The focus here has been one of partial equilibrium that allowed me to concentrate my attention on the firm level dynamics induced by self-discovery. It would be interesting to embed this mechanism in a general equilibrium model that would provide the framework for welfare analysis. In particular, a framework for welfare analysis would be necessary if secondary sources of learning, which here have been neglected, are incorporated into the discussion. There is some evidence that incumbent exporters provide informational spillovers for new export entrants (see Roberts and Tybout [1997] and Cadot et al. [2013]) and it would be interesting to include such secondary sources of firm learning as these informational spillovers
would warrant a normative analysis since there is a case for policy interventions that compensate exporters for the information externalities they generate.

Other extensions of the basic setup considered here would also be of interest to further understand the dynamics of firm level exports and the internationalization process of new exporters. First, while the decision to acquire information is endogenous in the model presented here, the amount of information acquired is not: all firms learn at the same rate. It would be interesting to incorporate self-discovery into the market penetration cost framework of Arkolakis [2010]. There, the endogenous choice of number of consumers reached by the firm can be linked to the amount of information acquired by the firm if it is assumed that each consumer provides an independent signal regarding the firm’s export profitability (see Akhmetova and Mitaritonna [2013] for an approach along these lines). Second, the extensive margin of number of destinations served is abstracted from. When export profitability is a persistent component that is global in scope, self-discovery could lead to a pattern of sequential expansion in export markets where the magnitude of first-year growth in export sales in a given destination depends on the time in the firm’s export tenure when that market was reached for the first time: first-year growth in export sales is stronger in destinations that are reached earlier on in the firm’s tenure in the export market. This pattern of sequential exporting is discussed and documented in Albornoz et al. [2012] for Argentinian exporters, and in chapter 2 for the case of Mexican exporters.


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Appendix
3.A Solving the Firm’s Dynamic Optimization Problem

In this section I provide a more thorough characterization of the firm’s dynamic optimization problem presented in section 3. It will be useful to work with a scaled version of the dynamic programming problem that defines the firm’s optimal policy. To that end, I define \( v_\theta := \frac{1}{\zeta} V_\theta \) and \( w_d := \frac{1}{\zeta} W_d \) and study the dynamic programming problem

\[
v_\theta (n, \mu, \epsilon) = \max_{d \in D} \{ w_d (n, \mu; \theta) + \epsilon_d \}.
\]

Under the assumptions presented in section 3 this dynamic optimization problem satisfies all of the assumptions of Theorem 3.1 in Rust [1988] (also see Rust [1994]), so the value function exists and is unique and the firm’s optimal policy can be determined from the Bellman equation representing the firm’s problem.

The assumptions made in section 3 allow for a more detailed characterization of the solution to the firm’s dynamic programming problem. Under the assumption that the unobserved state variables \( \epsilon \) are independent of the other state variables, the expected value function can be written as

\[
E [v_\theta (n', \mu', \epsilon') | n, \mu, d] = E_{\mu'} [E_{\epsilon'} [v_\theta (n + d, \mu', \epsilon') | n, \mu, d]].
\]

I define \( W_\theta (n', \mu') \equiv E_{\epsilon'} [v_\theta (n', \mu', \epsilon')] \), which allows me to write the expected value function as

\[
E [v_\theta (n', \mu', \epsilon') | n, \mu, d] = E_{\mu'} [W_\theta (n + d, \mu') | n, \mu, d].
\]

Under the distributional assumption for \( \epsilon \), the expected value function \( W_\theta (n, \mu) \) can be expressed as

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\[ W_\theta (n, \mu) = \ln \left[ \exp \left( w_0 (n, \mu; \vartheta) \right) + \exp \left( w_1 (n, \mu; \vartheta) \right) \right] , \]

where \( w_0 \) and \( w_1 \) are the alternative specific value functions.

I proof this claim in two steps. First, I proof that if \( \epsilon_i \overset{i.i.d.}{\sim} F_{EV} (\cdot; \gamma) \), where \( F_{EV} (x; \gamma) = \exp \left\{ - \exp \left\{ - (x + \gamma) \right\} \right\} \) is the CDF of an extreme value distribution with parameter \( \gamma \) equal to the Euler-Mascheroni constant (\( \approx 0.577 \)), and \( v_i \) are constants, then

\[ \max_i \{ v_i + \epsilon_i \} \sim F_{EV} \left( \cdot; \gamma - \log \left[ \sum_i \exp (v_i) \right] \right) , \]

with \( \mathbb{E} [\max_i \{ v_i + \epsilon_i \}] = \log [\sum_i \exp (v_i)] \).

Notice that

\[
\Pr \left( \max_i \{ v_i + \epsilon_i \} \leq x \right) = \Pr (v_1 + \epsilon_1 \leq x, \ldots, v_I + \epsilon_I \leq x) \\
= \prod_i \Pr (v_i + \epsilon_i \leq x) \text{ (by independence)} \\
= \prod_i \exp \left\{ - \exp \left\{ - (x + \gamma - v_i) \right\} \right\} \\
= \exp \left\{ - \sum_i \exp \left\{ - (x + \gamma - v_i) \right\} \right\} \\
= \exp \left\{ - \exp [- (x + \gamma)] \exp \left[ \log \sum_i e^{v_i} \right] \right\} \\
= \exp \left\{ - \exp \left\{ - (x + \xi) \right\} \right\} ,
\]

where \( \xi = \gamma - \log \sum_i e^{v_i} \). The last line is just the CDF for an extreme value distribution with parameter \( \xi \).

Now, if \( x \sim F_{EV} (\cdot; \gamma) \), then \( \mathbb{E} [x] = \delta - \gamma \), where \( \delta \) is the Euler-Mascheroni constant (thus, when \( \gamma \) is equal to the Euler-Mascheroni constant \( x \) has an expected value of
zero). Applying this result to the random variable \( \max_i \{ v_i + \epsilon_i \} \) we have that

\[
\mathbb{E} \left[ \max_i \{ v_i + \epsilon_i \} \right] = \delta - \xi = (\delta - \gamma) + \log \left[ \sum_i \exp (v_i) \right] = \log \left[ \sum_i \exp (v_i) \right],
\]

since \( \gamma \) is assumed to be equal to \( \delta \).

Finally, recall from section 3 that \( V_\theta (n, \mu, \epsilon) = \max_{d \in D} \{ w_d (n, \mu; \vartheta) + \epsilon_d \} \), so that applying this last result we have that

\[
W_\theta (n, \mu) = \mathbb{E}_\epsilon \left[ v_\theta (n, \mu, \epsilon) \right] = \mathbb{E}_\epsilon \left[ \max_{d \in D} \{ w_d (n, \mu; \vartheta) + \epsilon_d \} \right] = \ln \left[ \exp (w_0 (n, \mu; \vartheta)) + \exp (w_1 (n, \mu; \vartheta)) \right].
\]

If the firm decides to not serve the foreign market, then its state variables will remain at their current levels. That is, if \( d = 0 \), then \( n' = n \) and \( \mu' = \mu \). Therefore, in the case in which the firm decides not to export, the expected value function is given by

\[
\mathbb{E} \left[ v_\theta (n', \mu', \epsilon') | n, \mu, d = 0 \right] = W_\theta (n, \mu),
\]

which from the previous claim and the definition of the alternative specific value functions implies that the value of not exporting is given by

\[
W_0 (n, \mu; \vartheta) = \beta \ln \left[ \exp (w_0 (n, \mu; \vartheta)) + \exp (w_1 (n, \mu; \vartheta)) \right],
\]

which is just the discounted expected value of \( \max_{d \in D} \{ w_d (n, \mu; \vartheta) + \epsilon_d \} \).

For the alternative in which the firm chooses to export, we have that the output from the Kalman Filter implies the following conditional distribution:

\[
\mu' \sim N \left( \mu, \frac{\nu_\epsilon}{(\nu_\theta + n \nu_\epsilon)(\nu_\theta + (n + 1) \nu_\epsilon)} \right).
\]
Thus, in the case $d = 1$ the expected value function is given by

$$
\mathbb{E} [v_\theta (n', \mu', \epsilon') | n, \mu, d = 1] = \mathbb{E}_{\mu'} [W_\theta (n + d, \mu') | n, \mu, d = 1]
= \int_{-\infty}^{\infty} \ln \left[ \exp \left( w_0 (n + 1, \mu'; \vartheta) \right) + \exp \left( w_1 (n + 1, \mu'; \vartheta) \right) \right] f_\theta (\mu'|n, \mu) \, d\mu',
$$

where $f_\theta (\mu'|n, \mu)$ is the density of a Gaussian distribution with mean and standard deviation given as above.

From the definition of the alternative specific value functions, we have that the value of choosing to serve the foreign market is given by

$$
w_1 (n, \mu; \vartheta) = \zeta^{-1} \pi (n, \mu; \vartheta) + \beta \int_{-\infty}^{\infty} \ln \left[ \exp \left( w_0 (n + 1, \mu'; \vartheta) \right) + \exp \left( w_1 (n + 1, \mu'; \vartheta) \right) \right] f_\theta (\mu'|n, \mu) \, d\mu',
$$

the sum of expected current export profits and the discounted expected continuation value.

Therefore, the alternative specific value functions are the solution to the functional equations ($FE$):

$$
w_0 (n, \mu; \vartheta) = \beta \ln \left[ \exp \left( w_0 (n, \mu; \vartheta) \right) + \exp \left( w_1 (n, \mu; \vartheta) \right) \right],
$$

$$
w_1 (n, \mu; \vartheta) = \zeta^{-1} \pi (n, \mu; \vartheta) + \beta \int_{-\infty}^{\infty} \ln \left[ \exp \left( w_0 (n + 1, \mu'; \vartheta) \right) + \exp \left( w_1 (n + 1, \mu'; \vartheta) \right) \right] f_\theta (\mu'|n, \mu) \, d\mu'.
$$

These functional equations define a contraction mapping that possess a unique fixed point for $(w_0, w_1)$ as shown in Rust [1994]. From section 3 we know that the firm’s optimal policy is given by

$$
d^* = \mathbb{I} \left[ \delta (n, \mu; \vartheta) + \zeta \epsilon > 0 \right],
$$

where $\delta (n, \mu; \vartheta) = W_1 (n, \mu; \vartheta) - W_0 (n, \mu; \vartheta)$. Thus, to solve for the optimal policy function all that is required is to solve the above functional equations for the alternative specific functions $(w_0, w_1)$. 

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In section 3 it was shown that a crucial distinction between this dynamic model and static models of export supply is that the “exporter premia” in the dynamic model includes the “gains from trial”: the value that the firm attaches to gaining more precise information about its true profitability in the export market (information that can only be acquired by exporting). To further our intuition regarding the “gains from trial” or the option value of exporting, recall that for $d = 0$ the alternative specific value function was given by

$$w_0(n, \mu; \vartheta) = \beta \ln [\exp (w_0(n, \mu; \vartheta)) + \exp (w_1(n, \mu; \vartheta))],$$

thus I can re-write the above expression for $w_1$ as

$$w_1(n, \mu; \vartheta) = \zeta^{-1} \pi(n, \mu; \vartheta) + \int_{-\infty}^{\infty} w_0(n + 1, \mu'; \vartheta) f_\vartheta(\mu'|n, \mu) d\mu',$$

which in turn implies that

$$w_1(n, \mu; \vartheta) - w_0(n, \mu; \vartheta) = \zeta^{-1} \pi(n, \mu; \vartheta) + \int_{-\infty}^{\infty} [w_0(n + 1, \mu'; \vartheta) - w_0(n, \mu; \vartheta)] f_\vartheta(\mu'|n, \mu) d\mu'.$$

Thus, the “exporter premia” can be expressed as

$$\delta(n, \mu; \vartheta) \equiv \pi(n, \mu; \vartheta) + \int_{-\infty}^{\infty} [W_0(n + 1, \mu'; \vartheta) - W_0(n, \mu; \vartheta)] f_\vartheta(\mu'|n, \mu) d\mu',$$

from which we readily see that the “gains from trial” are given by

$$G(n, \mu; \vartheta) = \int_{-\infty}^{\infty} [W_0(n + 1, \mu'; \vartheta) - W_0(n, \mu; \vartheta)] f_\vartheta(\mu'|n, \mu) d\mu'.$$

By Taylor’s Theorem there exists $R(\cdot)$, a real-valued function, such that

$$W_0(n + 1, \mu'; \vartheta) = W_0(n + 1, \mu; \vartheta) + W_{0,\mu}(n + 1, \mu; \vartheta)(\mu' - \mu) + R(|\mu' - \mu|),$$

where

$$\lim_{\mu' \to \mu} R(|\mu' - \mu|) = 0.$$
Therefore, I can re-write the “gains from trial” as
\[
G(n, \mu; \vartheta) = \int_{-\infty}^{\infty} [W_0(n + 1, \mu; \vartheta) + W_{0, \mu}(n + 1, \mu; \vartheta)(\mu' - \mu) + R(|\mu' - \mu|) - W_0(n, \mu; \vartheta)] f_{\vartheta}(\mu'|n, \mu) d\mu'
\]
\[
= [W_0(n + 1, \mu; \vartheta) - W_0(n, \mu; \vartheta)] + W_{0, \mu}(n + 1, \mu; \vartheta) E_{f_{\vartheta}}[\mu' - \mu] + E_{f_{\vartheta}}[R(|\mu' - \mu|)],
\]
where \(E_{f_{\vartheta}}[\cdot]\) denotes the expectation taken with respect to the density \(f_{\vartheta}(\mu'|n, \mu)\).

Since \(\mu'\) has mean \(\mu\) under \(f_{\vartheta}(\mu'|n, \mu)\), the third term in the above expression drops out, and \(E_{f_{\vartheta}}[R(|\mu' - \mu|)]\) is “small” since most of the mass of \(f_{\vartheta}(\mu'|n, \mu)\) is concentrated around \(\mu\) and in that neighborhood \(R(|\mu' - \mu|)\) is close to zero. Thus, the “gains from trial” are approximately given by
\[
G(n, \mu; \vartheta) \simeq W_0(n + 1, \mu; \vartheta) - W_0(n, \mu; \vartheta).
\]
This is the expression presented in section 3.

3.B Numerical Solution to the Firm’s Dynamic Programming Problem

To characterize the optimal policy rule of the firm I need to solve for the alternative specific value functions \(w_0\) and \(w_1\), which are the solution to the functional equations:
\[
w_0(n, \mu; \vartheta) = \beta \ln [\exp (w_0(n, \mu; \vartheta)) + \exp (w_1(n, \mu; \vartheta))] + \pi(n, \mu; \vartheta) + \beta E \left[ \ln \left( \exp (w_0(n + 1, \mu'; \vartheta)) + \exp (w_1(n + 1, \mu'; \vartheta)) \right) \right] |n, \mu, d = 1,
\]
where \(E[\cdot|n, \mu, d = 1]\) denotes the expectation taken with respect to the density for
\[
\mu' \sim N \left( \mu, \frac{\nu \nu'_{\vartheta}}{(\nu_{\vartheta} + n \nu_{\vartheta}) (\nu_{\vartheta} + (n + 1) \nu_{\vartheta})} \right),
\]
which is the conditional distribution resulting from the signal extraction problem defined by the Kalman filter.

Observe that the functional equations defining $w_0$ and $w_1$ involve $w$ at both $n$ and $n+1$. Given that to solve for the exporter premium I will work with $N < \infty$, I need to make an assumption about the exporter premium at $N+1$. Since the underlying learning process implies that exporting will firms eventually learn their true export profitability, I impose that for sufficiently large $N$: $w(N, \mu; \vartheta) \simeq w(N+1, \mu; \vartheta)$. That is, I assume that for sufficiently large $N$ exporters have gathered enough information such that an additional export episode does not affect their perceived premium for exporting. Assumptions such as this are commonly used in the numerical solution of dynamic programming problems with unbounded state variables whose transition implies that the state variable must be non-decreasing. In practice I choose $N = 25$ to solve for the exporter premia.\(^\text{28}\) The results are not significantly different for $N = 20$ or $N = 30$.

I solve for the exporter premia numerically as follows: Let $N = \{0, 1, \ldots, N\} \subset \mathbb{N}$ and $G_{\mu} = \{-M \ldots, \mu_{-1}, \mu_0, \mu_1, \ldots M\} \subset \mathbb{R}$, where $\mu_0 = \mu_{\theta}$ and $M = \mu_{\theta} + 2.5\sigma_{\theta}$. The grid for the unobserved state variable $\mu$ defined by $G_{\mu}$ is such that I cover 99% of the mass for the initial prior distribution for the unknown export profitability $\theta$. I discretize the distributions implied by the Kalman filter over the grid $G_{\mu}$ to define transition matrices as follows:

\[
\Pr (\mu' = \mu_j | \mu = \mu_k, n, d = 0) = \mathbb{I} \{ j = k \}
\]
\[
\Pr (\mu' = \mu_j | \mu = \mu_k, n, d = 1) = \zeta \left[ \Phi \left( \frac{\Delta_{jk} + 0.5\Delta_j}{\sigma_n} \right) - \Phi \left( \frac{\Delta_{jk} - 0.5\Delta_{j-1}}{\sigma_n} \right) \right],
\]

\(^{28}\)What is important is that $N \gg T$, where $T$ is the number of time periods for which data is available in the sample.
where

\[
\Delta_{jk} \equiv \mu_j - \mu_k \\
\Delta_j \equiv \mu_{j+1} - \mu_j \\
\sigma_n \equiv \sqrt{\frac{\nu_{\xi}}{(\nu_{\theta} + n\nu_{\xi}) (\nu_{\theta} + (n + 1)\nu_{\xi})}}
\]

and \( \zeta \) is a normalizing constant such that \( \sum_j P_{kj}^n = 1 \).

Let \( J = |G_{\mu}| \), the number of grid points on the grid for the state variable \( \mu \), and let \( \pi(\vartheta) \) be an \( N \times J \) matrix with typical element

\[
\pi_{nj}(\vartheta) = \zeta^{-1} \tilde{\pi}(n - 1, \mu_j; \vartheta).
\]

The following algorithm solves numerically for the exporter premia:

Step 1 - Select an accuracy level \( \varepsilon > 0 \) and an initial guess \((w_{00}(\vartheta), w_{01}(\vartheta))\) which are \((N + 1) \times J\) matrices.

Step 2 - Functional equation step : use the functional equations defined above to solve for \((w_{00}^{m+1}(\vartheta), w_{10}^{m+1}(\vartheta))\).

For \( k = 1, \ldots, J \):

For \( n = 1, \ldots, N \) :

\[
\begin{align*}
  w_{0,nk}^{m+1} &= \beta \ln \left[ \exp(w_{0,nk}^m) + \exp(w_{1,nk}^m) \right] \\
  w_{1,nk}^{m+1} &= \pi_{nk}(\vartheta) + \beta \sum_j P_{kj}^n \ln \left[ \exp(w_{0,n+1j}^m) + \exp(w_{1,n+1j}^m) \right] \\
  w_{0,N+1k}^{m+1} &= w_{0,Nk}^m \\
  w_{1,N+1k}^{m+1} &= w_{1,Nk}^m.
\end{align*}
\]

\(^{29}\)To calculate the per period profits of the firm I need to evaluate the integral \( \mathbb{E}\left[ (h(\theta_t))^{\sigma} \mid \mu_t, n_t \right] \) that defines the risk-adjusted value of \( h(\cdot) \). I calculate this integral using the Gauss-Hermite quadrature method (see Judd [1999] for details).
Step 3 - End of iteration: If

$$\max \left\{ \max \left\{ \max \left\| u_{0,nj}^{m+1}(\vartheta) - w_{0,nj}^{m}(\vartheta) \right\|, \max \left\| w_{1,nj}^{m+1}(\vartheta) - w_{1,nj}^{m}(\vartheta) \right\| \right\} \leq \varepsilon \right.$$

stop; else, increment $m$ by 1 and return to step 2.

$\mathbb{P}^n$ is the $J \times J$ transition matrix with typical element

$$P_{k,j}^n = \text{Pr}(\mu' = \mu_j | \mu = \mu_k, n-1, d = 1) = \zeta \left[ \Phi \left( \frac{\Delta_{jk} + 0.5\Delta_j}{\sigma_{n-1}} \right) - \Phi \left( \frac{\Delta_{jk} - 0.5\Delta_j-1}{\sigma_{n-1}} \right) \right],$$

as outlined above.

Let $(\tilde{w}_0(\vartheta), \tilde{w}_1(\vartheta))$ denote the result from the this algorithm. I use these matrices to construct the exporter premium by: $\delta(\vartheta) = [\delta_{nj}] = [\zeta(\tilde{w}_{1,nj} - \tilde{w}_{0,nj})].$

### 3.C Estimation Procedure: Indirect Inference and Moment Matching

I estimate the model’s parameters using indirect inference as described in Gouriéroux and Monfort [2002]. I use the iterative procedure described in Dejong and Dave [2007] that proceeds as follows:

Step 1 - Select an accuracy level $\varepsilon > 0$ and an initial guess $\hat{\vartheta}_0$.

Step 2 - Weighting matrix step: Use $\hat{\vartheta}_j$ to construct

$$\Sigma_j = \frac{1}{S} \sum_{s=1}^{S} \left( m_s(\hat{\vartheta}_j) - \frac{1}{S} \sum_{s=1}^{S} m_s(\hat{\vartheta}_j) \right) \left( m_s(\hat{\vartheta}_j) - \frac{1}{S} \sum_{s=1}^{S} m_s(\hat{\vartheta}_j) \right)^t,$$

$$\Omega_j = \Sigma_j^{-1},$$

where $m_i(\hat{\vartheta}_j)$ is the $ith$ of $S$ realizations of model moments under the parameter vector $\hat{\vartheta}_j$. The matrix $\Omega_j$ is a symmetric non-negative matrix.
Step 3 - Minimization step: Find $\hat{\vartheta}_{j+1}$ as

$$
\hat{\vartheta}_{j+1} = \arg \min_{\vartheta} \left( \tilde{m}_d - \tilde{m} (\vartheta) \right)^T \Omega_j (\tilde{m}_d - \tilde{m} (\vartheta)).
$$

Step 4 - End of iteration: If $\|\hat{\vartheta}_{j+1} - \hat{\vartheta}_j\| < \varepsilon$, stop and set $\hat{\vartheta} = \hat{\vartheta}_{j+1}$; else, increment $j$ by 1 and return to step 2.

For the minimization step I use a simulated annealing algorithm.
Chapter 4

Labor Heterogeneity and the Pattern of Trade

4.1 Introduction

In this chapter I investigate the implications of the distribution of talent across workers on the international pattern of specialization. In particular, I test whether higher moments of a country’s skill distribution are an empirically important determinant of comparative advantage by combining data on trade flows with data from the International Adult Literacy Survey (IALS) that provides a direct measure of the educational capital relevant for workplace productivity held by a country’s working-age population. In contrast to previous work, I do not rely on measures of educational attainment to proxy for the distribution of talent in the population, instead I use IALS test scores to obtain a more direct measure of skills that can be used to construct a continuous distribution of talent, providing a more precise picture of the cross-country differences in endowments of workers at all skill levels.

Theories that emphasize relative factor differences as a source of comparative advantage are central to the classical theory of international trade. However, classical
factor proportions models fell out of favor given the lack of compelling empirical
evidence to support them, and due to the disproportionately high amount of inter-
national trade that takes place among industrialized countries. This last observation
contradicts what would be expected from factor proportions theory, since these coun-
tries share similar factor endowments and incomes per capita (see Deardorff [1984]).
Recent theoretical work has emphasized the role that worker heterogeneity can
play in determining comparative advantage. By focusing on subtler aspects of the
cross-country differences in factor supplies, models that emphasize the role of the
distribution of talent on comparative advantage can help rationalize both the large
volume of trade observed between developed countries, without appealing to returns
to scale, and the systematic pattern observed in these trade flows. As pointed out by
Grossman and Maggi [2000]

“It is well established that a country’s endowment of human capital is
an important determinant of the pattern of trade, but given that there are
systematic differences in the trading patterns of economies with similar
levels of development, physical capital, and human capital endowments
it is of interest to investigate whether the distribution of talent in the
workforce can play a role in the determination of the pattern of trade.”

There are two basic mechanisms through which higher moments of the skill distri-
bution matter for comparative advantage: worker sorting and matching. Models of
sorting, such as Ohnsorge and Trefler [2007] and Costinot and Vogel [2010], are based
on Roy-like assignment models (see Heckman and Honoré [1991], Sattinger [1993],
and Costinot and Vogel [2014]) in which workers are endogenously specific to the
industry that values their talent the most. In equilibrium, workers sort uniquely
into the industry in which their income is maximized. Differences in the relative
endowments of workers at different talent levels across two countries determine the
efficient division of production as in standard factor proportions models, here with
the notable difference that there is a continuum of factors of production. In this case, if country A’s distribution of talent is more dispersed than country B’s, then country A enjoys a relative abundance of both high and low skill workers, conferring to it a comparative advantage in those industries into which these type of workers sort into.

In models of matching, such as Grossman and Maggi [2000], workers produce output in teams, and industries vary by the degree of complementarity (or substitutability) that exists between the talent levels of the members who constitute a production team. In this type of model, the production technology is specified so as to emphasize the idea that the output of a production team depends on how talent is distributed across its members, rather than on the overall talent level of the production team. The distribution of talent across the workforce determines the relative supply of different production teams, and in this case if country A has a more dispersed skill distribution than country B, then country A has a relative abundance of production teams comprised of low and high talent levels, and thus should have a comparative advantage in industries where these type of production teams are relatively most productive.

So far, little to no attention has been paid to the empirical content of these theories. A notable exception is Bombardini et al [2012] which also provides evidence supporting the empirical relevance of the dispersion of skill in the working population as a source of comparative advantage. These authors focus on the theoretical mechanism linking a country’s skill distribution to the pattern of trade first outlined by Grossman and Maggi [2000]. However, the theoretical analysis of Bombardini et al.

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1Grossman and Maggi [2000] define complementarity in terms of “sub-modular” and “supermodular” production technologies. Supermodular production technologies are characterized by the fact that the marginal productivity of one worker is increasing in the talent level of the other workers in the production team. Submodular production technologies are characterized by the fact that the marginal productivity of a worker is decreasing in the talent level of other team members. Therefore, supermodularity applies when workers are complementary in creating value, while submodularity applies when workers are substitutable in creating value. For supermodular technologies, the efficient assignment of workers implies self-matching (i.e. production teams with members of similar talent levels). On the other hand, for submodular technologies, the efficient assignment of workers implies cross-matching (i.e. production teams whose members possess disparate talent levels).
al. differs from that in Grossman and Maggi in at least two important dimensions: 1. the focus is on the set of skills that are not easily observable ex-ante, so that random matching prevails along this dimension, and 2. all sectors are assumed to be super-modular, albeit to different degrees, so that all sectors benefit from assortative matching. Thus, these authors present evidence supporting the prediction that if (i) workers and firms randomly match along the unobservable component of skill, and (ii) industries vary in the degree in which they can substitute workers of different skills across production tasks, then firms in sectors with higher complementarity are relatively more productive in countries with lower skill dispersion.\(^2\)

In contrast to Bombardini et al. [2012], the focus of this study is on the comparative advantage predictions implied by the equilibrium sorting of workers to industries as in Costinot and Vogel [2010] since this provides a natural generalization of standard factor proportions models. The two fundamental comparative advantage predictions investigated here are: (i) skill abundant countries should export relatively more in skill intensive industries, and (ii) skill diverse countries should export relatively more in the most extreme industries in terms of skill intensity (i.e. export relatively more in both low and high-skill intensity sectors of production).\(^3\)

\(^2\)Under random matching the equilibrium distribution of workers within each firm is the same as the economy wide skill distribution. Since production functions are super-modular, mismatches between the talent levels of hired workers are costly in terms of productivity, and more so in those industries in which complementarity between the talent levels of the workforce are more important. More dispersed skill distributions result in a higher number of mismatches to prevail in equilibrium, and thus countries with dispersed talent distributions will have a comparative advantage in industries where complementarities are less important since mismatches will be relatively less costly in terms of forgone productivity.

\(^3\)These two correlations rest on the assumption that equilibrium in the labor market entails positive assortative matching. Let \(\{A(s, z) : z \in Z\}\) be the sector-specific productivities of a worker with skill level \(s\). Let

\[
A(s) = \{z \in Z : w(s, z) \geq w(s, z') \forall z' \neq z\},
\]

where \(w(s, z)\) are the earnings of an \(s\) type worker in industry \(z\). \(A(s)\) is the set of industries in which a type-\(s\) worker’s income is maximized. We say that there is positive assortative matching if \(a(s) = \inf A(s)\) and \(\pi(s) = \sup A(s)\) are weakly increasing in \(s\). That is, positive assortative matching implies that in equilibrium the most skilled workers are going to be found in the more skill intensive industries. Costinot and Vogel [2010] assume that \(A(s, z)\) is log-supermodular which is a sufficient condition for positive assortative matching to prevail in competitive equilibrium. Shimer
A final comment on the difference between the study of Bombardini et al. [2012] and the present study is in order. The fact that the former focus on a different channel through which skill dispersion can shape trade flows than the one under scrutiny in this study leads to important differences in the specification of the estimation framework used to test the relevant hypotheses. First, the measure of skill dispersion necessitated by their approach refers to the dispersion of the “unobservable” component of skills. Thus, their empirical counterpart of unobservable skills is approximated by purging IALS scores from the effect of a variety of observable individual characteristics to create a measure of “residual” skill dispersion. Secondly, the relevant industry characteristic for these authors is not skill intensity, as it is here, but rather skill complementarity (i.e. the degree of complementarity between the skill of workers across production tasks). Finally, the comparative advantage prediction studied by Bombardini et al. can be easily tested by specifying a covariate that is the interaction between skill dispersion (the exporter characteristic of interest) and skill complementarity (the relevant industry characteristic), while in the present case the estimation framework must specify a marginal effect of skill dispersion on trade flows that is non-linear as a function of skill intensity, since the comparative advantage prediction addressed here states that skill diverse countries will tend to specialize in both low-skill and high-skill intensive industries.

The two most challenging issues for the empirical analysis of the relationships between trade flows and worker heterogeneity that are the focus of this paper are: (a) the limited availability of internationally comparable data on the distribution of skills at the country level, and (b) constructing an index that adequately ranks industries in terms of skill intensity. Regarding the former, I use data from the IALS to proxy for the distribution of skills at the country level.\footnote{International Adult Literacy Survey (IALS), http://www.statcan.gc.ca/bsolc/olc-cel/olc-cel?catno=89M0014X&lang=eng} This survey tests the working age
population aged 16-65 on three key dimensions of literacy, which are meant to capture attributes relevant to productivity in the workplace. The advantage of this source of data over other literacy attainment surveys is that the data is continuous (test scores are reported in a scale ranging from 0 to 500) and the data is internationally comparable (see the Appendix for details). Regarding the latter issue, I use data from the BLS’s National Employment Matrix to obtain employment shares and average industry wages of Standard Occupation Classification (SOC) occupations, and the O*NET v.14 database to obtain data regarding the skill requirements of employed occupations.\(^5\) I use these two sources of data to construct measures of skill intensity at the industry level.

The results presented in section 4 lend support to the empirical validity of a generalized version of the standard \(2 \times 2 \times 2\) Heckscher-Ohlin Theorem: countries will tend to export goods that use relatively intensively their relatively abundant factors of production. According to the estimates, the distribution of skills explains more of the pattern of trade than countries’ endowment of capital and institutional features combined, at least for the set of exporters under consideration. The results also suggest that estimates found elsewhere in the literature (see, for example, Romalis [2004], Levchenko [2007] and Cuñat and Melitz [2010]) that find support for the hypothesis that capital abundant countries tend to specialize in capital intensive industries are sensitive to controlling for the effect of the distribution of talent on the pattern of trade.

The paper is organized as follows. Section 2 describes the estimation framework and its connection to models of international trade. Section 3 describes the data and carefully explains the classification of industries by skill intensity and the construction of the skill distribution at the country level. Section 4 reports the results from regression analysis, and section 5 concludes.

\(^5\)O*NET, http://www.onetonline.org/
4.2 From Theory to Estimation: The Relationship Between Trade Theory and the Estimation Framework

The theoretical importance of worker heterogeneity for comparative advantage has been well developed in the literature (see Grossman and Maggi [2001], Grossman [2004], Ohnsorge and Trefler [2007], Costinot and Vogel [2010], and Grossman et al. [2014]). Grossman [2013] provides a recent survey of the theoretical literature that incorporates heterogeneous labor into models of international trade. The way in which the distribution of skill across workers matters for comparative advantage through the sorting of workers into industries is a relatively straightforward extension of the insights of the standard factor proportions model. The objective of this paper is the empirical quantification of the generalized $2 \times 2 \times 2$ Heckscher-Ohlin predictions outlined in Costinot and Vogel [2010].

To fix ideas, let $f(s)$ and $h(s)$ denote the distribution of skills in countries A and B, respectively, so that the supply of workers at any skill level is given by $f(s)L_A$ in country A and $h(s)L_B$ in country B. For simplicity, assume that $L_A = L_B$, so that all differences in factor supplies are captured through the ratio $f(s)/h(s)$. Figure 4.1 depicts a situation in which the ratio $f(s)/h(s)$ is monotone decreasing in $s$. This implies that country B has a higher endowment of high-skill levels relative to A. Because country B is relatively well endowed with high-skilled workers, the cost of producing goods that use these type of workers should be low relative to A, and because whenever there is positive assortative matching high-skill workers sort into skill intense sectors, country B should have a comparative advantage in these sectors.

On the other hand, Figure 4.2 depicts a situation in which the ratio $f(s)/h(s)$ is first monotone increasing, but after some point $\hat{s}$ the ratio is monotone decreasing. This situation corresponds to the case in which country B is relatively well endowed
with both very low and very high-skilled workers. If positive assortative matching prevails in equilibrium, the cost of producing goods in the extreme sectors is relatively low for country B, and this should confer to it a comparative advantage in both low-skill and high-skill intensity industries relative to country A.

In the remainder of this section I develop the estimation framework that will be used to assess the merits of the comparative advantage predictions outlined above. As Deardorff [1984] points out

“The major obstacle to the testing of trade theories has been the difficulty of constructing tests that all would agree were theoretically sound. The intuitive content of most trade theories is quite simple and straightforward. But empirical tests of the theories are often faulted on the grounds that they test propositions that do not derive rigorously from the theories.”

In this section I provide an informal derivation of a relationship between trade flows and importer, exporter, and industry characteristics that form the basis for the estimation framework that will be used in section 4. The main objective of this
derivation is to make explicit the ways in which the empirical framework is linked to the theory.

Assume that preferences are given by a two-tier CES structure:

\[
U = \int_0^1 \alpha(z) \ln [Q(z)] \, dz
\]

\[
Q(z) = \left( \int_{\omega_z \in \Omega_z} q(\omega_z)^{\frac{\sigma-1}{\sigma}} \, d\omega_z \right)^{\frac{\sigma}{\sigma-1}}
\]

with \( \int_0^1 \alpha(z) \, dz = 1 \). Here, the first tier is a Cobb-Douglas utility index over consumption bundles \( Q(z) \) from different sectors, indexed \( z \in [0, 1] \), and the second tier is a CES aggregator over different varieties within each sector. The parameter \( \sigma > 1 \), is the elasticity of substitution across varieties, assumed common across sectors, and \( \Omega_z \) is the set of available varieties in sector \( z \).

This preference structure leads to the following expression for the expenditures of country \( i \) on a variety from sector \( z \)

\[
e_i(\omega_z) = D_{iz} p_i(\omega_z)^{1-\sigma}.
\]

Here, \( p_i(\omega_z) \) is the price paid in \( i \) for a variety in sector \( z \), and \( D_{iz} \) captures the strength of demand in country \( i \) for varieties in sector \( z \).

Given the above expression for expenditures, trade volumes are given by the following expression

\[
X_{ijz} = M_{jz} D_{iz} p_{ijz}^{1-\sigma},
\]

\( \footnote{The strength of demand \( D_{iz} \) depends on: (a) the CES ideal price index for sector \( z \) in country \( i \), \( P_{iz} = \left( \int_{\omega_z \in \Omega_z} p_i(\omega_z)^{1-\sigma} \, d\omega_z \right)^{\frac{1}{1-\sigma}} \); (b) the share of income spent on goods from sector \( z \), \( \alpha(z) \), and (c) the income of country \( i \).} \)
where $X_{ijz}$ are the imports of country $i$, from country $j$, in sector $z$; $p_{ijz}$ is the price paid by consumers in $i$ for a variety from country $j$ in sector $z$, and $M_{jz}$ is the mass of firms in the exporting country in industry $z$.

On the production side, assume that final goods are produced by monopolistically competitive firms. The unique factor of production for these firms is a sector specific composite input that is assumed to be non-traded and produced competitively by a constant returns to scale technology. Given the demand structure outlined above, optimal pricing by final good producers results in a constant markup over marginal cost:

$$p_{ijz} = \left( \frac{\sigma}{\sigma - 1} \right) \tau_{ijz} c_{jz},$$

where $c_{jz}$ is the cost of the sector specific composite in country $j$, and $\tau_{ijz}$ are the trade barriers faced by country $j$ in sector $z$ when servicing demand from country $i$.

Finally, assume that $\tau_{ijz}^{-\sigma} = (T_{ij} \cdot T_{iz}) e^{-u_{ijz}}$, where $u_{ijz} \sim N(0, \sigma^2)$ are i.i.d. unobserved/unmeasured trade barriers. Given this assumption, and the optimal pricing strategy of final good producers, trade flows may be expressed as

$$X_{ijz} = M_{jz} D_{iz} p_{ijz}^{-\sigma}$$

$$= M_{jz} D_{iz} \left( \frac{\sigma}{\sigma - 1} \right)^{1-\sigma} c_{jz}^{1-\sigma} (T_{ij} \cdot T_{iz})^{-1} e^{-u_{ijz}}.$$

Taking logs on both sides of this expression yields

$$\log (X_{ijz}) = \log \left[ \left( \frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \right] + \log (D_{iz}) - \log (T_{iz}) - \log (T_{ij}) + \log (M_{jz} c_{jz}^{1-\sigma}) + u_{ijz},$$

which suggests the expression

$$\log (X_{ijz}) = \lambda_{iz} + \lambda_{ij} + \log (M_{jz} c_{jz}^{1-\sigma}) + u_{ijz},$$
where $\lambda_{iz}$ is an importer-industry specific term, and $\lambda_{ij}$ is an importer-exporter specific term.

Notice that this expression has the following implication for the distribution of relative exports across sectors:

$$
E \left[ \log \left( \frac{X_{ijz}}{X_{ikz}} \right) - \log \left( \frac{X_{ijz'}}{X_{ikz'}} \right) \right] = (\sigma - 1) \left[ \log \left( \frac{c_{jz}}{c_{kz}} \right) - \log \left( \frac{c_{jz'}}{c_{kz'}} \right) \right] + \left[ \log \left( \frac{M_{jz}}{M_{kz}} \right) - \log \left( \frac{M_{jz'}}{M_{kz'}} \right) \right].
$$

This expression relates the distribution of relative exports to two terms: the first, which refers only to relative costs of production, is tied to comparative advantage, while the second term comes from the endogenous adjustment in the entry and exit of firms to achieve equilibrium.

In two-country models of international trade it is not too hard to show that

$$
\log \left( \frac{c_{jz'}}{c_{kz'}} \right) - \log \left( \frac{c_{jz}}{c_{kz}} \right) > 0 \Rightarrow \log \left( \frac{M_{jz}}{M_{kz}} \right) - \log \left( \frac{M_{jz'}}{M_{kz'}} \right) > 0.
$$

That is, there is relatively more entry into the comparative advantage sectors.\(^7\) Thus, in a two-country model of international trade both forces point in the same direction. In general, the intuition that the relative mass of firms $M_{jz}/M_{kz}$ should be decreasing in relative costs of production $c_{jz}/c_{kz}$ is not easy to extend to a multi-country model, specially when countries are asymmetric. In a multi-country setup, third country effects crucially affect production patterns.\(^8\) Therefore, the desired result is not generally valid and must either be assumed, or derived under stringent conditions. Since the equilibrium distribution of firms across countries and sectors is such that there remains no further possibility for profitable entry, assuming that the relative mass of firms $M_{jz}/M_{kz}$ is decreasing in relative costs $c_{jz}/c_{kz}$ may prove innocuous to

\(^7\)See, for example, Romalis [2004]. Although this author considers a multi-country model, in his setup the world is divided into North and South countries with all countries homogeneous within each block. Thus, the model is essentially a two-country model of international trade. See also Bernard, Redding, and Schott [2007].

\(^8\)See Behrens et. al. [2009].
the extent that it is not unreasonable to expect that entry is relatively higher in those sectors where a country enjoys a comparative advantage. Here I will proceed under the assumption that this is indeed the case.

A fully specified general equilibrium model will provide a mapping from exporter and industry characteristics to the mass of firms and the cost of the industry specific composite input. That is,

$$\log(M_{jz}c_{jz}^{1-\sigma}) = f(\text{characteristics of exporter } j, \text{characteristics of sector } z).$$

For example, in the model of Romalis [2004], $c_{jz}$ is given by

$$c_{jz} = (\omega_j)^z$$

where $\omega_j$ is the relative price of skilled to unskilled labor, and $z$ is the cost share of skilled labor in the sector (i.e. $z$ is the sector’s skill intensity). Because of transport costs, there is a failure of factor price equalization (FPE) and in equilibrium

$$\omega_j = \omega\left(\frac{L^s_j}{L^u_j}\right),$$

where $L^s/L^u$ is the relative endowment of skilled to unskilled labor. In this way, Romalis is able to derive the three way relationship between trade, factor endowments, and factor intensities necessary to test the trade implications of a standard factor proportions model.

It should be clear that the most important part in deriving the estimating equation of interest is the way in which the term $\log(M_{jz}c_{jz}^{1-\sigma})$ is modeled, since this is the term that is germane to the theory of comparative advantage. I do not specify a full general equilibrium model, but given the previous discussion, here I have chosen to model the term of interest as

$$\log(M_{jz}c_{jz}^{1-\sigma}) = W_{jz} \delta + g(s_z, \mu_j, \sigma_j) + \epsilon_{ijz},$$

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so that the expression for trade flows is given as

$$\log (X_{ijz}) = \lambda_{iz} + \lambda_{ij} + W_{jz}\delta + g(s_z, \mu_j, \sigma_j) + \varepsilon_{ijz},$$

where $\varepsilon_{ijz} = \epsilon_{ijz} + u_{ijz}$.

This specification is parsimonious in the way in which alternative sources of comparative advantage affect trade flows (i.e. $W_{jz}\delta$ controls linearly for alternative source of comparative advantage), while allowing for more flexibility in the way in which the distribution of talent affects the pattern of trade. Of course, this is only a heuristic derivation, and it is worthwhile to point out that in a fully specified model $\log (M_{jz}^{1-\sigma})$ might be a complicated, highly nonlinear object. Thus, the specification that is being proposed should be interpreted with care, and estimated coefficients should be interpreted as those for the best approximation to the true CDF $\mathbb{E} [\log (M_{jz}^{1-\sigma}) | X]$ within a given class of functions.

The above derivation suggests that the estimating equation should have importer-industry and importer-exporter fixed effects, rather than separate industry, importer, and exporter fixed effects. However, due to the computational complexity of estimating importer-industry and importer-exporter fixed effects, I replace these with separate industry, importer, and exporter fixed effects.\footnote{Estimating importer-industry and importer-exporter fixed effects would require close to 19,000 dummy variables given the number of exporters and industries included in the sample, while including separate importer, exporter, and industry fixed effects requires about 300 dummy variables only.} Thus, I arrive at the following estimation framework:

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz}\delta + g(s_z, \mu_j, \sigma_j) + \varepsilon_{ijz},$$

where $x_{ijz}$ is the log of average exports from $j$ to $i$ in industry $z$ over the period 1996-2000; $\sigma_j$ is the log of the standard deviation of the skill distribution in $j$; $\mu_j$ is the log of the mean of the skill distribution in $j$; $s_z$ is a measure of the skill
intensity of sector $z$; $W_{jz}$ is a set of covariates that could potentially affect trade flows differentially across exporter-industry pairs (for example, alternative sources of comparative advantage), and the $\lambda$'s are importer, exporter, and industry fixed effects. The left-hand variable is taken as the average trade flow over a 5 year window, rather than for a specific year, to smooth out the effects of any year-to-year fluctuations in the distribution of exports across sectors.

This formulation explains exports through the interaction of industry-level characteristics and country-level characteristics. The effect of exporter characteristics on the volume of trade across all industries is captured by the exporter fixed effect. The terms $W_{jz}\delta$ and $g(s, \mu_j, \sigma_j)$ capture the effect of exporter characteristics on the pattern, but not the volume, of trade. The aim of the empirical framework is to identify whether a given correlation, derived in the context of a two-country model, is present in the data. The estimating equation is specified in such a way that it tests whether the correlation of interest holds when comparing the relative exports of two exporters into a third market. Conditions under which such a test would be theoretically justified are outlined in the online Appendix.

To gain further insight into the logic behind the estimation framework and the way it is related to the comparative advantage predictions derived from theoretical models, suppose that we assume $g(s, \mu, \sigma) = \gamma (\mu \times s) + \sigma \cdot \tilde{g}(s)$ and consider two exporters that are identical except for the mean of their skill distributions. Then, it is easy to see that the estimating equation implies

$$
\mathbb{E} \left[ (x_{ijz} - x_{ij'z'}) - (x_{ij'z} - x_{ij'z'}) \mid W_{jz} = W_{j'z'}, \sigma_j = \sigma_{j'} \right] = \gamma (\mu_j - \mu_{j'}) (s_z - s_{z'}) .
$$

The expression above relates the exports of exporters $j$ and $j'$, in industries $z$ and $z'$, to a common destination $i$. If $j$ is more skill abundant than $j'$ ($\mu_j > \mu_{j'}$), and $z$ is more skill intense than $z'$ ($s_z > s_{z'}$), then theory suggests that we should expect to
see $\gamma > 0$ (i.e. the positive coefficient would indicate that countries more abundant in high-skill workers should export relatively more in skill intensive industries).

On the other hand, consider two exporters that are identical except for the standard deviation of their skill distributions. Then, the estimating equation readily implies

$$E[x_{ijz} - x_{ij'z}|W_{jz} = W_{j'z}, \mu_j = \mu_{j'}] = (\lambda_j - \lambda_{j'}) + (\sigma_j - \sigma_{j'}) \cdot \tilde{g}(s_z).$$

This expression makes it clear that the exporter fixed effects capture differences in the volume of trade common to all sectors, and that variation across industries in relative exports between $j$ and $j'$ to export destination $i$ is captured through the function $\tilde{g}(s_z)$. The discussion preceding Figure 4.2 suggests that if $j$ is more skill diverse than $j'$ (i.e. $\sigma_j > \sigma_{j'}$), then $\tilde{g}(\cdot)$ should be a $U$-shaped function (opening upward). That is, conditional on both $j$ and $j'$ exporting to $i$, then the more skill diverse country should command a higher share of country $i$'s expenditures in both low-skill and high-skill intensive industries.

This estimation framework has become standard in the international trade literature. Romalis [2004] uses a version of this estimation framework to test for the importance of capital endowments, both physical and human, in the determination of the pattern of trade. More recently, Levchenko [2007] has used this framework to show that countries with better institutions have a comparative advantage in goods that are institutionally dependent; Nunn [2007] has also used this framework to show that exporters with better contract enforcement specialize in the production of goods for which relationship-specific investments are important, while Cuñat and Melitz [2010] have used it to assess the importance of labor market institutions as a source of comparative advantage. These reduced form estimation frameworks contrast with the more structural approach developed by Chor [2010] who extends
the framework of Eaton and Kortum [2002] to quantify the importance of different sources of comparative advantage.

The results provided in section 4 cannot be taken as conclusive evidence of the effect of the distribution of talent on the pattern of trade for a number of reasons. First, it is possible that estimated coefficients are biased due to the omission of important determinants of the pattern of trade. If any terms that are correlated with the variables of interest have been omitted, then estimates will be biased. In my estimation I include in $W_{jz}$ a set of covariates that control for a host of alternative determinants of the variation in exports across different industries in an attempt to address this concern as carefully as possible. Another reason to be cautious about the estimates provided in section 4 is that important non-linearities may have been omitted from the estimating equation. For example, so far the literature has neglected capital-labor complementarities that may affect worker sorting, and it is possible that such complementarities would imply important non-linearities that are being omitted from the analysis here. This issue is addressed, to some extent, in section 4.

Before proceeding to the discussion of the results from regression analysis, section 3 describes the data and explains in detail both the construction of the measure of skill intensity at the industry level and the construction of the distribution of skills at the country level.

4.3 The Data

Data on bilateral trade flows are taken from Feenstra et.al. [2005]. I convert the original trade data that are classified by 4-digit SITC Rev.2 codes to the NAICS 1997 4-digit classification. The final data comprise 84 industries that include both manufacturing and non-manufacturing industries. The 84 industries included in the sample are those for which the BLS’s National Employment Matrix accounts for at
least 80% of industry employment. While this threshold of 80% is arbitrary, for reasons that will become apparent shortly, it is necessary to restrict attention to industries where most of the division of employment across occupations is accounted for. Within this set of industries the employment coverage ranges from a minimum of 80% to a maximum of 98% of industry employment, and the median employment coverage is 93.5% of industry employment. 729 SOC occupations are represented within these 84 industries.

As alternative determinants of the pattern of trade, I control for standard factor proportions as in Romalis [2004], and institutional sources of comparative advantage as in Cuñat and Melitz [2010] and Nunn [2007]. Data on contract enforcement quality and relationship-specificity at the industry level are from Nunn [2007]. Data on the flexibility of labor markets and industry volatility are taken from Cuñat and Melitz [2010]. Data on countries’ stock of physical capital are from the Penn World Tables, and I use the natural log of the average capital endowment over the period 1997-2000 as my measure of capital abundance. Because data on capital endowments are not available for either the Czech Republic or Slovenia, when I control for this source of comparative advantage the number of exporters in the sample falls from 19 to 17. Data on capital intensities are from the NBER CES Manufacturing Database for the year 2000. Because this source of data only covers manufacturing industries, the number of industries falls from 84 to 76 when I control for the effect of capital abundance on the pattern of trade. Further details regarding the data can be found in section 6.
Measuring Skills: The IALS Data

The novel exporter characteristic under investigation here is the distribution of skills at the country level. In this subsection I describe in detail the construction of the skill distribution for each exporter in the sample.  

The data regarding a country’s skill distribution is obtained from the International Adult Literacy Survey (IALS), which provides the first internationally comparable data on literacy attainment for the working age population aged 16-65. This survey was implemented in 20 countries\(^1\), which account for over 50 percent of the world’s entire gross domestic product. Of these 20 countries, all except Australia have made their survey results publicly available.

The IALS data provides \textit{reliable} and \textit{comparable} estimates of the \textit{levels} and \textit{distribution} of literacy skills in the adult population.\(^2\) Most previous studies have defined literacy in a binary way: either the person was literate or not. Furthermore, many of these surveys suffer from the unfortunate drawback that testing procedures are not standardized across countries, making it difficult to make cross-country comparisons.

\(^{10}\)In the literature, “skill” is just a short-hand for the ability of workers to generate output. We are thus interested in the distribution of workplace productivity in the workforce, and it might be cause for concern whether the variable that has been denoted as skill is in fact the relevant measure of labor productivity of who’s distribution we care about. That is, it could well be the case that the labor productivity that matters for production is \(a = f(s)\), not \(s\) directly, and the object of interest would be the distribution of \(a\) in the population, not of \(s\). I will be particularly interested in comparisons of the first two moments of the distribution of \(s\). In this case, if \(E[s_i] \geq E[s_j]\), then \(E[a_i] \geq E[a_j]\) for any monotone increasing function \(f(\cdot)\). On the other hand, if \(\text{Var}(s_i) \geq \text{Var}(s_j)\), then \(\text{Var}(a_i) \geq \text{Var}(a_j)\) iff \(f(\cdot)\) is such that

\[
E[(f(s_i) + f(s_j)) (f(s_i) - f(s_j))] \geq (E[f(s_i)] + E[f(s_j)]) (E[f(s_i)] - E[f(s_j)]).
\]

There is little that can be done to address this kind of misspecification, and I proceed under the assumption that \(f(\cdot)\) satisfies the conditions stated above so that observed productivity differences \(s\) are informative about the determinants of the pattern of trade, and about the importance of labor heterogeneity as a determinant of comparative advantage.

\(^{11}\)The participating countries are: Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden, Switzerland, United Kingdom, and the United States.

\(^{12}\)The number of survey participants in each country ranges from 2062 to 6718, with the average number of participants being 3378.
In the IALS dataset, proficiency levels are measured along a continuum (test scores range from 0 to 500) and denote how well adults use information to function in society and the economy. That is, literacy is defined as

“the ability to understand and employ printed information in daily activities, at home, at work, and in the community - to achieve one’s goals, and to develop one’s knowledge and potential” - *Literacy in the Information Age - Final Report of the International Adult Literacy Survey*, OECD Publications.

The IALS collects data on three dimensions of literacy that can be used to approximate skills:

1. **Prose Literacy**: represents the knowledge and skills needed to understand and use information from texts. In this domain, subjects where tested on three aspects relevant to information processing: *locating, integrating,* and *generating*. Locating tasks ask the subject to find information in the text based on conditions or features specified in the question or directive. Integrating tasks ask the subject to pull together two or more pieces of information in the text. Finally, generating tasks require the subject to produce a written response by processing information from the text and by making text-based inferences or drawing on their own background knowledge.

2. **Document Literacy**: represents the knowledge and skills required to locate and use information contained in various formats. Within this domain, subjects are tested on four aspects relevant to the processing of information contained in documents: *locating, cycling, integrating* and *generating*. Locating tasks require the reader to match one or more features of information stated in the question to either identical or synonymous information given in the document. Cycling tasks ask the reader to locate and match one or more features of
Table 4.1: Variability in test score for IALS

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>sd (Prose)</td>
<td>16.64</td>
<td>0</td>
<td>87.06</td>
</tr>
<tr>
<td>sd (Document)</td>
<td>17.57</td>
<td>0</td>
<td>96.08</td>
</tr>
<tr>
<td>sd (Quantitative)</td>
<td>17.83</td>
<td>0</td>
<td>95.23</td>
</tr>
</tbody>
</table>

information, but differ from locating tasks in that they require the reader to engage in a series of feature matches to satisfy conditions given in the question. The integrating tasks typically require the reader to compare and contrast information in adjacent parts of the document. In the generating tasks, readers must produce a written response by processing information found in the document and by making text-based inferences or drawing on their own background knowledge.

3. *Quantitative Literacy*: represents the knowledge and skills required to apply arithmetic operations, either alone or sequentially, to numbers embedded in printed materials, such as balancing a checkbook, figuring out a tip, completing an order from or determining the amount of interest on a loan from an advertisement.

The IALS also goes to great lengths to minimize measurement error in order to obtain a more accurate assessment of a subject’s underlying capabilities. Each text subject is administered the IALS exam five times. For each test subject I will work with the average score across these five observations. However, to get a sense of the variation in test scores present in the data, for each test subject I compute the standard deviation of test scores in each of the three dimensions of literacy being assessed. Table 4.1 presents summary statistics for this measure of variability in test scores. As can be seen, for some test subject there is no variation in test scores across the five replications of the test.
Table 4.2: IALS Summary Statistics

Table 4.2 summarizes the IALS data.\textsuperscript{13} The last three columns in Table 4.2 display the correlations across the three dimensions of literacy tested by the IALS. As can be observed, all of these dimensions of literacy are highly correlated.

To gain further insight into the relationship between these different dimensions of literacy, I consider simple regressions of one of these variables on the other two:\textsuperscript{14}

\[
\text{Prose} = 33.58^{***} + 0.63^{***}\text{Document} + 0.23^{***}\text{Quantitative} \quad (R^2 = 0.88)
\]

\[
\text{Document} = -8.61^{***} + 0.46^{***}\text{Prose} + 0.56^{***}\text{Quantitative} \quad (R^2 = 0.93)
\]

\[
\text{Quantitative} = 10.56^{***} + 0.23^{***}\text{Prose} + 0.75^{***}\text{Document} \quad (R^2 = 0.9)
\]

\textsuperscript{13}µ denotes mean, σ denotes standard deviation, and ρ denotes correlation.
\textsuperscript{14}*** denotes statistical significance at the 0.1 percent level.
These regressions suggest that any of these three dimensions of literacy is well explained by the other two, and that there is a positive, and statistically significant, relationship between any of these three dimensions of literacy and the other two.

The sample correlations presented in Table 4.2, and the results from simple regression analysis, suggest that these three dimensions of literacy in fact contain much redundant information. Therefore, it seems appropriate to consolidate these different literacy scores into a single variable that I will call “skill”. I define the variable “skill” as

\[
\text{Skill} = \omega_p \text{Prose} + \omega_d \text{Document} + \omega_q \text{Quantitative},
\]

where the weights \((\omega_p, \omega_d, \omega_q)\) are chosen through principal component analysis.\(^{15}\)

The weights \((\omega_p, \omega_d, \omega_q)\) are the weights corresponding to the first component from PCA performed on the IALS survey data.\(^{16}\) PCA is particularly appropriate when the original variables are highly correlated - suggesting a certain degree of redundancy in the information contained by these variables - , which is the case here as can be verified in Table 4.2. Table 4.3 presents summary statistics for the skill distribution constructed in this fashion.\(^{17}\)

I also perform kernel density estimation to obtain densities for the skill distribution. The estimation is performed using the “Normal Reference Rule” (see Silverman [1998] and Wasserman [2006] for details). Selected results are presented in Figure 4.7.

---

\(15\)From an initial set of \(m\) correlated variables, principal component analysis (PCA) creates uncorrelated indices or components, where each component is a linear weighted combination of the initial variables. Being uncorrelated, the indices measure different dimensions of the data. The components are ordered so that the first component \((PC_1)\) explains the largest possible amount of variation in the original data.

\(16\)Actually, since the weights from principal component analysis do not sum to one - the sum of their squares does - , I normalize the weights so that they sum to unity. This, additionally, makes sure that the change of basis that is involved in PCA does not affect the range of potentially observable skill levels (i.e. the skill variable remains in the range \([0, 500]\)).

\(17\)Weights are chosen independently across countries. That is, I perform a principal components analysis on the data of each country individually. The weights across the three dimensions of literacy are roughly equal, with quantitative literacy typically receiving a slightly higher weight, and the weights on these three variables are roughly the same across countries.
<table>
<thead>
<tr>
<th>Country</th>
<th>$\mu$</th>
<th>$\sigma$</th>
<th>$\sigma/\mu$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>287.6</td>
<td>50.64</td>
<td>0.18</td>
</tr>
<tr>
<td>Canada</td>
<td>258.8</td>
<td>65.01</td>
<td>0.25</td>
</tr>
<tr>
<td>Chile</td>
<td>207.6</td>
<td>58.74</td>
<td>0.28</td>
</tr>
<tr>
<td>Czech Rep.</td>
<td>287.6</td>
<td>46.07</td>
<td>0.16</td>
</tr>
<tr>
<td>Denmark</td>
<td>291.7</td>
<td>40.29</td>
<td>0.13</td>
</tr>
<tr>
<td>Finland</td>
<td>289.6</td>
<td>47.37</td>
<td>0.16</td>
</tr>
<tr>
<td>Germany</td>
<td>283.8</td>
<td>42.74</td>
<td>0.15</td>
</tr>
<tr>
<td>Hungary</td>
<td>251.9</td>
<td>48.39</td>
<td>0.19</td>
</tr>
<tr>
<td>Ireland</td>
<td>261.6</td>
<td>57.06</td>
<td>0.22</td>
</tr>
<tr>
<td>Italy</td>
<td>252.8</td>
<td>57.94</td>
<td>0.23</td>
</tr>
<tr>
<td>Netherlands</td>
<td>284.4</td>
<td>45.23</td>
<td>0.16</td>
</tr>
<tr>
<td>New Zealand</td>
<td>277.8</td>
<td>51.51</td>
<td>0.19</td>
</tr>
<tr>
<td>Norway</td>
<td>295.9</td>
<td>46.57</td>
<td>0.16</td>
</tr>
<tr>
<td>Poland</td>
<td>228.6</td>
<td>64.84</td>
<td>0.28</td>
</tr>
<tr>
<td>Slovenia</td>
<td>234.9</td>
<td>62.05</td>
<td>0.26</td>
</tr>
<tr>
<td>Sweden</td>
<td>297.6</td>
<td>52.74</td>
<td>0.18</td>
</tr>
<tr>
<td>Switzerland</td>
<td>273.2</td>
<td>55.52</td>
<td>0.20</td>
</tr>
<tr>
<td>UK</td>
<td>266.5</td>
<td>62.04114</td>
<td>0.23</td>
</tr>
<tr>
<td>USA</td>
<td>258.7</td>
<td>71.13</td>
<td>0.27</td>
</tr>
</tbody>
</table>

Coefficient of Variation 0.09 0.16 0.24

Table 4.3: Summary Statistics for Skill Distribution
Figure 4.3: USA

Figure 4.4: Switzerland

Figure 4.5: Denmark

Figure 4.6: Germany

Figure 4.7: Kernel Density Estimates of Skill Distribution
The most salient features arising from this construction of the skill distribution are: (i) There is an apparent trade-off between mean and standard deviation; (ii) The skill distribution is relatively “bell shaped” although with a slightly positive bias (i.e. the left tail is longer than the right tail); (iii) For four of the nineteen countries, the skill distribution is bimodal. This suggests the possibility that for these countries the overall skill distribution is in fact the mixture of the skill distribution for two separate populations, and (iv) The countries with the most dispersed skill distribution are Anglo-Saxon countries, while the countries with the highest mean skill levels are typically Scandinavian countries. This confirms results presented in Bomardini et al. [2009] and Grossman and Maggi [2000].

Additionally, Table 4.3 also indicates that countries at similar stages of development can exhibit substantial differences in the degree of skill dispersion amongst its workforce: the USA and Canada display a more dispersed skill distribution than, for example, Germany and Denmark. The last row of Table 4.3 reports the coefficient of variation for the exporter characteristic of interest, and it can be readily seen that for the set of exporters under consideration, differences in the distribution of human capital are more pronounced for the higher moments of the distribution than for the mean, which has traditionally been the focus of the empirical trade literature.

The reasons why the distribution of skill in the workforce differs across countries at similar stages of development falls beyond the scope of this study. I take this country characteristics as given, and investigate how it shapes the pattern of trade at a given point in time. Unfortunately, the sensitivity of the results to alternative measures of the distribution of skills cannot be easily checked, as other sources of data on literacy attainment suffer from limitations that make them inadequate for the purposes of this paper.

Brown et. al [2007] discuss the robust features of literacy attainment surveys. One of their main findings is that one of the most robust features arising from the different
literacy attainment surveys currently available, is the apparent trade-off between mean and standard deviation, that is, there is a negative relationship between mean scores and their dispersion. Regression analysis confirms that there is a statistically significant negative relationship between these two variables. It is estimated that a 10 percent decrease in the standard deviation of the distribution of skills results in a 4 percent decrease in the mean skill level.\(^{18}\)

The standard source in the literature for measures of skill at the country level has been the Barro-Lee database on international data on educational attainment (see Barro and Lee [2001]), so a brief comparison of the measures of skill provided there and the measure of skill proposed here is warranted. There are at least two reasons why the measure of skill based on the IALS data proposed here is preferable to the data available from the Barro-Lee database. First, years of schooling is a noisy measurement of a person’s underlying productivity in the workforce. As Barro and Lee [2001] note themselves

> “Although the test scores of students reflect the quality of schooling and, hence, indicate the quality of the labor force, they do not directly measure the educational capital held by a country’s working-age population. Knowledge can be gained or lost after the completion of formal education. Ideally, tests of cognitive ability would be administered to adults, as well as to students.”

The IALS is aimed precisely at addressing this issue, since it is designed to elicit certain work-related skills in the adult population. As mentioned above, the IALS data contains three measures of literacy, thus recognizing the multifaceted nature of literacy and has made great efforts to measure skills directly in the adult population in a manner that is consistent across countries so that cross-country comparisons of these measures of skill are meaningful. In addition, the IALS has strived to minimize

\[ \log (\mu) = 7.1621^{***} - 0.3962^{**} \log (\sigma) \quad (R^2 = 0.4156) \]

\(^{18}\)
measurement error by having each test subject take the exam on multiple occasions. The final score that I use for each of these subjects is his or her average score across replications, which should provide a more accurate measurement of an individual’s underlying skill level.

Second, the primary focus of the Barro-Lee data is to provide adequate measures of the human capital stock available as an input into production. Their data provides the distribution of educational attainment of the population aged 15 and over at seven levels of schooling. Given that the focus here is in understanding the effects on the pattern of trade of the subtler cross-country differences in factor endowments that arise from differences in the distribution of talent in the workforce, this level of aggregation might prove undesirable. Of course, the severe limitation of the IALS data, in contrast to the Barro-Lee data, is the limited availability of data given that only 20 countries currently participate in the survey, most of which are OECD countries, and only 19 of them make their data publicly available. This severely limits the set of exporters that can be included in the sample.

**Measuring Industry Skill Intensity: The BLS and O*Net Data**

The final variable of interest to estimate the effect of skill abundance and skill diversity on the pattern of trade is a measure of skill intensity at the industry level. To construct this measure I use data from the National Employment Matrix for 2006, available from the Bureau of Labor Statistics, and the O*NET database on occupational descriptors. The National Employment Matrix provides detailed employment information for 4-digit NAICS industries. This matrix provides a breakdown of industry employment across Standard Occupation Classification (SOC) occupations, as well as industry wage data for these occupations. The O*NET database provides information on occupational descriptors, which include skill requirements for over 800 SOC occupations. For several of these occupational descriptors the O*NET database reports *importance*
and *level ratings*. As the names suggests, the “importance” dimension rates whether a particular worker attribute is important in a given occupation, while the “level” dimension rates the level of this attribute required to perform the occupation.¹⁹

For each of the 729 SOC occupations represented in the sample, I obtain standardized scores from the O*NET v.14 database for the following occupational descriptors concerning an occupation’s skill requirements:

1. **Speaking**: Talking to others to convey information effectively.

2. **Writing**: Communicating effectively in writing as appropriate for the needs of the audience.

3. **Mathematics**: Using mathematics to solve problems.

4. **Reading Comprehension**: Understanding written sentences and paragraphs in work related documents.

Using these descriptors, for each occupation I calculate a *skill relevance* score as

\[
R^\text{skill}_k = \omega_s R_s + \omega_w R_w + \omega_m R_m + \omega_{rc} R_{rc}
\]

\[
R_k = \frac{\text{Importance}_k \times \text{Level}_k}{10,000},
\]

where the weights \((\omega_s, \omega_w, \omega_m, \omega_{rc})\) are chosen using principal components analysis.²⁰ This skill relevance score is an index between 0 and 1 that summarizes the skill level that a worker must have to perform efficiently in a given occupation. For each descriptor \(k\), the score \(R_k\) is an index between 0 and 1, with \(R_k = 1\) if and only if both the importance *and* level ratings are scored at their maximum level, and \(R_k = 0\) if and only if the descriptor \(k\) is deemed “Not Relevant” for the occupation.²¹ Table

---

¹⁹For example, both lawyers and legal clerks are given the same importance rating for the skill attribute “reading comprehension”. However, they differ in that lawyers are required to have a higher level of this skill than legal clerks do.

²⁰The results do not vary significantly if equal weights are given to each descriptor.

²¹This property provides the rationale behind the definition of \(R_k\) in terms of the interaction of the level and importance ratings.
### Bottom 10 Occupations

<table>
<thead>
<tr>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crossing Guards</td>
</tr>
<tr>
<td>Graders and Sorters, Agricultural Products</td>
</tr>
<tr>
<td>Sewing Machine Operators</td>
</tr>
<tr>
<td>Logging Equipment Operators</td>
</tr>
<tr>
<td>Cleaners of Vehicles and Equipment</td>
</tr>
<tr>
<td>Locomotive Firers</td>
</tr>
<tr>
<td>Pressers, Textile, Garment, and Related Materials</td>
</tr>
<tr>
<td>Meat, Poultry, and Fish Cutters and Trimmers</td>
</tr>
<tr>
<td>Earth Drillers, Except Oil and Gas</td>
</tr>
</tbody>
</table>

### Top 10 Occupations

<table>
<thead>
<tr>
<th>Anthropology and Archeology Teachers (p.s.)*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental Science Teachers (p.s.)</td>
</tr>
<tr>
<td>Engineering Teachers (p.s.)</td>
</tr>
<tr>
<td>Nursing Instructors and Teachers (p.s.)</td>
</tr>
<tr>
<td>Atmospheric, Earth, Marine, and Space Sciences Teachers (p.s.)</td>
</tr>
<tr>
<td>Forestry and Conservation Science Teachers (p.s.)</td>
</tr>
<tr>
<td>Criminal Justice and Law Enforcement Teachers (p.s.)</td>
</tr>
<tr>
<td>Health Specialties Teachers (p.s.)</td>
</tr>
<tr>
<td>Sociologists</td>
</tr>
<tr>
<td>Area, Ethnic, and Cultural Studies Teachers (p.s.)</td>
</tr>
</tbody>
</table>

*(p.s.)=Postsecondary

#### Table 4.4: Ranking of SOC Occupations in Terms of Skill Requirements

4.4 reports the bottom ten occupations (in ascending order of skill relevance score), and the top ten occupations (in descending order of skill relevance score) that result from this construction.

Based on these skill relevance scores for SOC occupations, I measure skill intensity at the industry level as

\[
\begin{align*}
    s_z &= \prod_{i \in O_z} R_i^\alpha_{iz} \\
    \alpha_{iz} &= \frac{w_{iz}L_{iz}}{\sum_{j \in O_z} w_{jz}L_{jz}},
\end{align*}
\]

where \( R_i \) is occupation \( i \)'s skill relevance score, \( O_z \) is the set of occupations employed in industry \( z \), and \( \alpha_{iz} \) is occupation \( i \)'s share in labor costs in industry \( z \), where \( w_{iz} \) is occupation \( i \)'s average yearly wage in industry \( z \) and \( L_{iz} \) is employment of occupation \( i \) in industry \( z \). Both \( w_{iz} \) and \( L_{iz} \) are from the BLS National Employment Matrix for the year 2006. This measure is a geometric average of the skill levels of those occupations employed in the industry, weighted by their “factor intensity” or cost.
Table 4.5: Ranking of Industries by Skill Intensity

<table>
<thead>
<tr>
<th>Industry Name</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computer and Peripheral Equipment Manufacturing</td>
<td>1</td>
</tr>
<tr>
<td>Pharmaceutical and Medicine Manufacturing</td>
<td>2</td>
</tr>
<tr>
<td>Communications Equipment Manufacturing</td>
<td>3</td>
</tr>
<tr>
<td>Navigational, Measuring, Electromedical, and Control Instruments Manufacturing</td>
<td>4</td>
</tr>
<tr>
<td>Oil and Gas Extraction</td>
<td>5</td>
</tr>
<tr>
<td>Other Textile Product Mills</td>
<td>80</td>
</tr>
<tr>
<td>Cut and Sew Apparel Manufacturing</td>
<td>81</td>
</tr>
<tr>
<td>Animal Slaughtering and Processing</td>
<td>82</td>
</tr>
<tr>
<td>Apparel Accessories and Other Apparel Manufacturing</td>
<td>83</td>
</tr>
<tr>
<td>Logging</td>
<td>84</td>
</tr>
</tbody>
</table>

Given the novel construction of this proxy, I now undertakes several external validation exercises to investigate whether the measure $s_z$ provides a reasonable measure of skill intensity at the industry level. To investigate this issue I first consider the relationship between $s_z$ and industry wages. Let $\bar{w}_z$ be the average wage in industry $z$. I consider a regression of average industry wage on skill intensity, allowing for a non-linear effect of skill intensity on average wages:

$$\ln (\bar{w}_z) = 10.18^{***} - .22^{**} s_z + 1.58^{***} s_z^2 \quad (R^2 = 0.82).$$

\(^{22}\) Results are not affected if skill intensity is defined as the arithmetic average $s_z = \sum_{i \in O_z} a_{iz} R_i$. 

\(^{23}\) A higher rank number corresponds to a lower skill intensity (i.e. the number 1 ranked industry is the most skill intensive industry, while the number 84 ranked industry is the least skill intensive industry).

\(^{24}\) Average wages is another commonly used measure of skill intensity at the industry level.
The results show a positive, and statistically significant, relationship between average industry wages and skill intensity as measured by $s_z$. This relationship is more clearly depicted in Figure 4.8.

Next, I consider the wage regression

$$w_{ij} = \lambda_i + \gamma_i (D_i \times \ln (R_j)) + \epsilon_{ij},$$

where $w_{ij}$ is the log average wage of occupation $j$ in industry $i$, $\lambda_i$ is an industry fixed effect, $D_i$ is an industry dummy, and $R_j$ is occupation $j$’s skill relevance score. This wage regression implies that the marginal effect of an increase in skills varies by industry:

$$\frac{\partial w_{ij}}{\partial \ln (R_j)} = \gamma_i.$$

A similar exercise, but with the dependent variable being the coefficient of variation of industry wages, shows that there is no statistically significant relationship between wage dispersion and skill intensity as measured by $s_z$. If industries also varied by the degree of complementarity in production of different labor inputs, and we believed $s_z$ to be possibly reflecting this varying degree of complementarity across industries, then we would expect to observe a relationship between $s_z$ and industry wage dispersion.
To the extent that it is reasonable to belief that more skill intensive industries are more willing to pay for high skilled workers, we should expect to see a strong positive association between $\gamma_z$ and $s_z$. Indeed this is the case, the correlation between the $\gamma$’s and the skill intensity $s_z$ is equal to 0.68, confirming that skills are more highly rewarded in skill intensive industries.

The measure proposed here for skill intensity at the industry level is novel in that it is constructed from detailed employment data and skill requirements at the occupation level. In the literature it is standard to proxy a sector’s skill intensity by the ratio of non-production worker wages to total payroll, and it might be of interest to compare $s_z$ to this more standard measure of a sector’s skill intensity. Let $h_z$ denote the standard measure of skill intensity. Then, the correlation between these two measures is 0.72. That is, roughly speaking, these two indices of skill intensity rank industries in the same manner. However, one potential advantage of the measure $s_z$ is that it does not a priori assume that non-production occupations require more skill than production occupations. This assumption may prove innocuous, specially for industries in the manufacturing sector, but the measure $s_z$ avoids making these judgements and directly looks at who is employed in a sector and what are the skill requirements of those workers.

Table 4.6 below presents correlations between the rankings for different industry characteristics. As can be seen, the skill intensity ranking $s_z$ is positively correlated with all other industry characteristics, and in particular exhibits a relatively strong positive correlation with capital intensity. The correlations between capital intensity, volatility, and relationship specificity are of the same sign and of comparable magnitude to those reported elsewhere (see Cuñat and Melitz [2010] and Nunn [2007]).

I assume that industry-specific characteristics computed for the United States also apply to industries in other countries. This assumption is standard in the recent empirical trade literature on comparative advantage (see, for example, Cuñat and
<table>
<thead>
<tr>
<th>Industry Characteristic</th>
<th>Capital Intensity</th>
<th>Volatility</th>
<th>Rel. Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skill Intensity</td>
<td>0.54</td>
<td>0.18</td>
<td>0.11</td>
</tr>
<tr>
<td>Capital Intensity</td>
<td>-</td>
<td>-0.02</td>
<td>-0.34</td>
</tr>
<tr>
<td>Volatility</td>
<td>-</td>
<td>-</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Table 4.6: Correlations Between Industry Characteristics

Melitz [2010] and Nunn [2007]), and is justified if to the extent that countries have access to the same technologies. For the set of exporters under consideration this assumption does not seem unreasonable. However, this claim is not easily verified due to the lack of publicly available data with similar sector classification from countries other than the United States, and I must rely on the commonly used assumption that the ranking of measures does not vary across countries.

4.4 Empirical Results

In this section I present the results of estimating the regression framework outlined in section 2.

4.4.1 Examining the Raw Data

Before turning to the results from regression analysis, in this section I give an overview of the raw data. Table 4.7 reports the distribution of exports across low-skill intensity sectors, medium-skill intensity sectors, and high-skill intensity sectors. Theory suggests that the relative exports of a skill diverse country, vis-à-vis a less diverse country, should be concentrated in the low and high-skill intensity sectors, while the

---

26 Even with access to the same technologies, if factor prices vary across countries, then factor intensities measured as cost shares will vary across countries (see Davis and Weinstein [2001]). However, Davis and Weinstein also point out that the observed differences in input usage by industry across countries may result from the aggregation of goods of heterogeneous factor content within industry categories, rather than a failure of factor price equalization. Here, as in other empirical studies on the determinants of the pattern of trade (i.e. Romalis [2004], Levchenko [2007], Nunn [2007]), I do not address this issue, but merely acknowledge that my findings may be tarnished if this proves to be a significant issue for the sample under consideration.
<table>
<thead>
<tr>
<th>Country</th>
<th>Low Skill</th>
<th>Medium Skill</th>
<th>High Skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>0.27</td>
<td>0.22</td>
<td>0.51</td>
</tr>
<tr>
<td>Canada</td>
<td>0.39</td>
<td>0.19</td>
<td>0.42</td>
</tr>
<tr>
<td>Chile</td>
<td>0.41</td>
<td>0.48</td>
<td>0.11</td>
</tr>
<tr>
<td>Czech Rep.</td>
<td>0.36</td>
<td>0.31</td>
<td>0.33</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.28</td>
<td>0.26</td>
<td>0.46</td>
</tr>
<tr>
<td>Finland</td>
<td>0.42</td>
<td>0.2</td>
<td>0.38</td>
</tr>
<tr>
<td>Germany</td>
<td>0.23</td>
<td>0.24</td>
<td>0.53</td>
</tr>
<tr>
<td>Hungary</td>
<td>0.35</td>
<td>0.21</td>
<td>0.44</td>
</tr>
<tr>
<td>Ireland</td>
<td>0.11</td>
<td>0.11</td>
<td>0.78</td>
</tr>
<tr>
<td>Italy</td>
<td>0.26</td>
<td>0.36</td>
<td>0.38</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.20</td>
<td>0.18</td>
<td>0.62</td>
</tr>
<tr>
<td>New Zealand</td>
<td>0.59</td>
<td>0.23</td>
<td>0.18</td>
</tr>
<tr>
<td>Norway</td>
<td>0.16</td>
<td>0.10</td>
<td>0.74</td>
</tr>
<tr>
<td>Poland</td>
<td>0.42</td>
<td>0.35</td>
<td>0.23</td>
</tr>
<tr>
<td>Slovenia</td>
<td>0.40</td>
<td>0.29</td>
<td>0.31</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.37</td>
<td>0.20</td>
<td>0.43</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.09</td>
<td>0.17</td>
<td>0.74</td>
</tr>
<tr>
<td>UK</td>
<td>0.14</td>
<td>0.20</td>
<td>0.66</td>
</tr>
<tr>
<td>USA</td>
<td>0.18</td>
<td>0.18</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Table 4.7: Distribution of Exports

Relative exports of the less diverse country should be concentrated in the medium-skill intensity sectors. That is, relative exports should display a U-shaped pattern as we move from low to high-skill intensity sectors.

The type of exercise I am interested in relates the quantity

\[
\frac{X_{ijz}}{X_{iFz}} \times \frac{X_{ijz}}{X_{iFz}}
\]

where \(X_{ijz}\) is the trade flow from \(j\) to \(i\) in industry \(z\), to exporter and industry characteristics. Figure 4.9 compares the distribution of exports between selected exporter pairs. The selected pairs, which are all comparable in size in terms of GDP per capita, present the U-shaped pattern predicted by theory for exporters who differ in terms of skill diversity. However, as can be discerned from Table 4.7, this pattern is not evident in the raw data for all exporter pairs in the sample.
Closer inspection of the export shares in Table 4.7 suggests that “richer” countries have larger export shares in high skill intensity sectors. Indeed, in the sample the correlation between the share of high-skill intensity exports and the level of development (measured by the log of the average GDP per capita between 1998-2000) is 0.75. If high-quality goods are characterized by skill-intensive technologies, then the recent literature suggesting a positive association between per capita income and the quality of exports (see, for example, Fajgelbaum et al. [2011]) can account for this observed correlation. This also suggests that controlling for the way in which the level of development affects the pattern of trade may prove important for the empirical exercise considered here.

4.4.2 Results from Regression Analysis

I now turn to the results from regression analysis. Recall that the estimation framework is given by

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz} \delta + g(s_z, \mu_j, \sigma_j) + \varepsilon_{ijz}.$$  

In this section I will discuss the results from different modeling assumptions regarding the term $g(s_z, \mu_j, \sigma_j)$, which captures the effect of skill abundance (through the
mean skill level) and of skill diversity (through the standard deviation of the skill distribution) on the trade pattern across industries that vary in their skill intensity. Because I do not include observations where no exports are recorded for a given exporter-importer-industry triplet, the results that follow should be interpreted as capturing the pattern of comparative advantage for countries across all of its export sectors, and not the effect of comparative advantage on the country-level decision to export in a particular sector.\footnote{That is, I exclude observations that record zero trade flows so that the analysis is focused on the pattern of comparative advantage conditional on exporting.}

The vector $W_{jz}$ controls for alternative sources of variation in the pattern of trade. It includes the interaction term $K_j \times k_z$ to control for the effects of capital abundance on the pattern of trade. Here $K_j$ is the natural log of the average capital stock per worker over the period 1998-2000 and capital intensity $k_z$ is proxied by one minus the ratio of total payroll to value added.\footnote{This measure of capital intensity is used by Romalis [2004] and Nunn [2007]. Results do not vary significantly if alternative measures of capital intensity are use such as the log of of the ratio of the real capital stock to number of production workers.} Also included are the interaction terms $F_j \times v_z$ and $F_j \times k_z$, where $F_j$ and $v_z$ are labor market flexibility and industry volatility as in Cuñat and Melitz [2010], that control for labor market flexibility as a source of comparative advantage, and the interaction term $CE_j \times rs_z$, where $CE_j$ is a measure of contract enforcement and $rs_z$ is relationship-specificity, that controls for institutional determinants of the pattern of trade as in Nunn [2007]. Finally, in some of the specifications to be discussed, the vector $W_{jz}$ also includes controls for the effect of the level of development on the pattern of trade.

My baseline specification for the estimating equation is

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz} \delta + \beta_0 (\mu_j \times s_z) + \beta_1 (\sigma_j \times s_z) + \beta_2 (\sigma_j \times s_z^2) + \varepsilon_{ijz}.$$
a linear marginal effect, where we would expect $\beta_0 > 0$, capturing the intuition that increases in skill abundance should have larger marginal effects on skill intensive industries. The interactions $\sigma_j \times s_z$ and $\sigma_j \times s_z^2$ specify a non-linear marginal effect of skill diversity in exports:

$$\frac{\partial E[x_{ijz}]}{\partial \sigma_j} = \beta_1 s_z + \beta_2 s_z^2,$$

where, according to theory, we should expect $\beta_2 > 0$. A positive coefficient on $\beta_2$ would reflect that increases in skill diversity should benefit low skill intensive and high skill intensive sectors relatively more.

As is common in practice I consider a series of short and long regressions. First, I estimate the short regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \beta_0 (\mu_j \times s_z) + \beta_1 (\sigma_j \times s_z) + \beta_2 (\sigma_j \times s_z^2) + \varepsilon_{ijz},$$

and then proceed to a series of long regressions. OLS estimates are reported in Table 4.8.

Column (1) estimates the short regression on the full sample. In this specification data are available for 84 industries, and 19 exporters that export to 185 destinations. The estimated coefficients $\hat{\beta}_0$ and $\hat{\beta}_2$ are positive, and statistically significant. These estimates provide evidence in favor of the hypotheses that: (a) skill abundant countries specialize in skill intensive industries, and (b) skill diversity confers a comparative advantage in both low and high-skill intensity industries.

Next, I control for capital endowments and institutional sources of comparative advantage. Because capital endowment data in unavailable for Slovenia and the Czech Republic, and because capital intensities are only available for manufacturing industries, the sub-sample on which the long-regression is estimated includes 76 industries, and 17 exporters that export to 184 export destinations. In column
Table 4.8: The Determinants of Comparative Advantage

(2) of Table 4.8, I first re-estimate the short-regression using this smaller sample of exporters and industries. The coefficient on the interaction $\mu_j \times s_z$ is of roughly the same magnitude, and retains its statistical significance. On the other hand, the coefficient on the interaction $\sigma_j \times s_z^2$ looses much of its magnitude, and all of its statistical significance.

In column (3) of Table 4.8 I control for the effect of capital endowments by introducing the interaction term $K_j \times k_z$, and for the institutional sources of comparative advantage by introducing the interaction terms $F_j \times v_z$, $F_j \times K_z$ and $CE_j \times r_s_z$, where the former control for the effect of labor market flexibility on the pattern of trade, and the latter controls for contract enforcement as a source of comparative advantage. The estimate for $\beta_0$ is of similar magnitude to that in column (2), and of the same statistical significance. Notice that after controlling for alternative sources of comparative advantage, the estimate for $\beta_1$ gains in magnitude and statistical significance. The estimate for $\beta_2$ remains statistically insignificant.
Finally, I add two sets of controls that if omitted may bias the estimated importance of the distribution of talent for comparative advantage. One set includes the interaction of country capital abundance $K_j$ with sector factor intensity $s_z$. This controls for the possibility that capital abundance, through its effect on factor prices, affects specialization differentially across industries varying in terms of skill intensity. The other is a set of interaction terms $y_j \times D_z$, where $D_z$ is an industry dummy and $y_j$ is the log of average GDP per capita over the period 1998-2000 in country $j$. These interaction terms allow for the level of development to affect trade in each individual sector differentially in an unrestricted way. This specification is more general than, for example, adding interaction terms between $y_j$ and individual sector characteristics such as value added, TFP growth, input variety, etc. as done by some authors (see, for example, Nunn[2007]). These additional interactions control for other country-level determinants of the pattern of trade.

These last set of results are reported in columns (4) – (6) in Table 4.8. The addition of the interaction term $K_j \times s_z$, as can be seen in column (4), does not affect the statistical significance of the estimates for $\beta_0$ or $\beta_1$, although the estimate for $\beta_0$ observes a substantial drop in its magnitude. The estimate for $\beta_2$, although positive, remains statistically insignificant. The estimates in column (5) show that controlling for the effect of the level of development on the pattern of trade strongly affects the magnitude of the predictions for the distribution of talent as a source of comparative advantage: the estimates for $\beta = (\beta_0, \beta_1, \beta_2)'$ drop substantially. In particular, the estimate for $\beta_0$ drops significantly as compared to its estimate in column (3), although it loses none of its statistical significance. However, notice that the estimate for $\beta_1$ does lose all of its statistical significance.

Because I report standardized beta coefficients, one can directly compare the relative magnitude of the effects of the distribution of skills on the pattern of trade with those of alternative determinants of comparative advantage. According to the
estimates in column (3), the effect that the distribution of talent has on the pattern of trade is greater than the combined effects of both capital and institutional sources of comparative advantage. Of particular significance, notice that skill abundance is an economically significant determinant of the pattern of trade: a one standard deviation increase in the interaction term $\mu_j \times s_z$ increases the dependent variable by 6.24 standard deviations, while a simultaneous one standard deviation increase in the interaction terms $F_j \times v_z$, $F_j \times k_z$, and $CE_j \times r_s z$, that correspond to institutional sources of comparative advantage, only increase the dependent variable by 0.78 standard deviations. Observe also, that increasing the interaction term $\sigma_j \times s_z$ by one standard deviation has a greater impact on the dependent variable than the combined effect of institutional determinants of comparative advantage. Thus, both skill abundance and skill diversity appear to be economically significant determinants of the pattern of trade.

An interesting issue arises concerning the estimates of the coefficient on the interaction term $K_j \times k_z$. Notice from columns (3)–(6) in Table 4.8, that the estimated coefficient on the interaction term $K_j \times k_z$, although highly statistically significant, is of a sign opposite to what would be expected from the traditional comparative advantage prediction based on capital abundance and capital intensity. That is, while it would be expected that more capital abundant countries should export relatively more in capital intensive industries, the estimate here suggests otherwise. This is at odds with findings elsewhere in the literature. 29

I explore this result by running the short-regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \beta_0 (K_j \times k_z) + \beta_1 (F_j \times v_z) + \beta_2 (F_j \times k_z) + \beta_3 (CE_j \times r_s z) + \varepsilon_{ijz}. $$

29 See, for example, Romalis [2004], Levchenko [2007], Nunn [2007], and Cuñat and Melitz [2010], who all find a positive estimated coefficient for this covariate.
The standardized coefficient on the interaction $K_j \times k_z$ is $\hat{\beta}_0 = -0.1253$, which is negative but not statistically significant at conventional levels. That $\beta_0$ is not statistically different from zero might not be surprising considering that the sample under consideration includes only 17 exporters, most of which are OECD countries and most of which are classified as “Northern” countries by Romalis [2004].\textsuperscript{30} For these subset of countries, differences in endowments of physical capital have been argued to play no significant role in the determination of the pattern of trade (see Deardorff [1984]). Therefore, it is interesting to note that once I control for the effect of the distribution of talent on the pattern of trade, the coefficient on the interaction $K_j \times k_z$ remains negative, but gains in statistical significance.\textsuperscript{31} This anomalous result is hard to interpret and may possibly suggest that more attention needs to be paid to the modeling of the complementarity relationships that may exist between physical capital and workers of heterogeneous talent levels.

The estimates reported in Table 4.8 provide support for both the hypotheses that skill abundance and skill diversity are economically, and statistically, significant determinants of the pattern of trade. However, the estimates from Table 4.8 find weak support to the hypothesis that skill diverse countries tend to export relatively more in both low and high-skill intensive sectors. Although the estimate for $\beta_2$ is in all cases positive, it is not statistically significant at any of the conventional levels. There is, however, strong evidence for a hypothesis that would posit that skill diversity induces specialization in skill intensive industries. Furthermore, these estimates suggest that, within this group of exporters, the distribution of talent in the workforce is a more economically substantial determinant of the pattern of trade than institutional factors.

\textsuperscript{30}Romalis classifies a country as belonging to the “North” if its GDP per capita, at purchasing power parity, is at least 50 percent of the U.S. level. 14 out of the 17 exporters under consideration in this estimation belong to the “North” under this classification.

\textsuperscript{31}In columns (3) – (6) in Table 4.8, the estimated coefficient on this covariate is statistically significant at the 0.1 percent level.
or more traditional determinants of comparative advantage such as endowments of physical capital.

4.4.3 “Accounting” for the Variation in Trade Flows

The reported standardized coefficients of Table 4.8 provide information regarding the relative importance of each of the determinants of the pattern of trade, to the extent that they quantify the impact of changing a specific covariate on the dependent variable. However, it is also of interest to assess how much of the variation in the dependent variable can be attributed to each of the independent variables of interest. In this section I discuss a number of results whose aim is to provide some understanding of which of the determinants of the pattern of trade account for more of the observed variation in trade flows.

Consider the baseline estimating equation

\[ x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \beta_1 W_{1jz} + \beta_2 W_{2jz} + \ldots + \beta_k W_{kjz} + \varepsilon_{ijz}, \]

where \( \bar{W}_{jz} = (W_{1jz}, \ldots, W_{kjz}) \) are covariates that affect the pattern of trade. For each regressor \( W_{hjz} \) I run the auxiliary regressions

\[ x_{ij} = \lambda_i + \lambda_j + \lambda_z + W_{-hjz} \beta_{-h} + \epsilon_{ijz} \]
\[ W_{hjz} = \lambda_i + \lambda_j + \lambda_z + W_{-hjz} \beta_{-h} + \omega_{hjz}, \]

where \( W_{-hjz} \) is the vector of covariates \( \bar{W}_{jz} \) excluding the \( h^{th} \) explanatory variable.

From each of these auxiliary regressions I take residuals to run the regression

\[ \hat{\epsilon}_h = \delta_h \hat{\omega}_h + \zeta, \]
where $\hat{\epsilon}_h$ is the residual from the regression of exports on fixed effects and all determinants of the pattern of trade except the $h^{th}$ explanatory variable, and $\hat{\omega}_h$ is the residual from the regression of the $h^{th}$ explanatory variable on fixed effects and all other determinants of the pattern of trade. The standardized coefficient from this last regression is equal to the partial correlation between the independent variable (i.e. the trade flow) and the dependent variable $h$. That is, the beta coefficient from this last regression is a measure of the mutual relationship between $x_{ijz}$ and $W_{hjz}$ when all other variables are held constant with respect to the two variables $x_{ijz}$ and $W_{hjz}$. Additionally, the $R^2$ from this last regression is a measure of the proportion of the unexplained variance in $x_{ijz}$ that is explained by the part of $W_{hjz}$ that is orthogonal to all other covariates. Thus, the $R^2$ from this regression provides a measure of the variation in the independent variable that can be explained by the $h^{th}$ explanatory variable alone. Table 4.9 reports the results. These partial correlations largely confirm the relationships implied by the estimates of Table 4.8.

Next, I consider the construction of $R^2$ increments for each explanatory variable. The $h^{th}$’s variable $R^2$ increment is defined as $R^2 - R^2_h$, where $R^2_h$ is the coefficient of determination from the regression with the $h^{th}$ variable omitted, and $R^2$ is the

<table>
<thead>
<tr>
<th>$h^{th}$ explanatory variable</th>
<th>$\delta$</th>
<th>Partial $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_j \times s_z$</td>
<td>0.015***</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td></td>
</tr>
<tr>
<td>$\sigma_j \times s_z$</td>
<td>0.007*</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td></td>
</tr>
<tr>
<td>$\sigma_j \times s_z^2$</td>
<td>-0.028***</td>
<td>0.0008</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td></td>
</tr>
<tr>
<td>$K_j \times k_z$</td>
<td>-0.023***</td>
<td>0.0005</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td></td>
</tr>
<tr>
<td>$F_j \times v_z$</td>
<td>0.120</td>
<td>0.0144</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td></td>
</tr>
<tr>
<td>$F_j \times k_z$</td>
<td>0.028***</td>
<td>0.0008</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td></td>
</tr>
<tr>
<td>$CE_{ij} \times rs_z$</td>
<td>-0.0024</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.9: Partial Correlations and Partial $R^2$’s

Standard errors in parentheses. *, **, and *** denote significance at the 5, 1 and 0.1 levels, respectively.
coefficient of determination from the full regression. It can be shown that the $R^2$ increment for the $h^{th}$ variable may be expressed as

$$R^2 - R_h^2 = r_h^2 (1 - R_h^2),$$

where $r_h$ is the sample correlation between the $h^{th}$ variable and the dependent variable (see Theil [1971] for details). The above expression states that the incremental contribution of the $h^{th}$ variable in accounting for the variation in the dependent variable increases as the absolute value of the partial correlation between the dependent and $h^{th}$ variable increases. However, the contribution of the $h^{th}$ variable decreases when the other $k - 1$ variables account for a larger proportion of the variation of the dependent variable.

Table 4.10 presents the percent increase\(^{32}\) in $R^2$ for the regression

$$\hat{x}_{ijz} = \hat{W}_{jz} + \hat{\beta}_0 (\hat{\mu}_j \times \hat{s}_z) + \hat{\beta}_1 (\hat{\sigma}_j \times \hat{s}_z) + \hat{\beta}_2 (\hat{\sigma}_j^2 \times \hat{s}_z^2) + \varepsilon_{ijz},$$

where hatted variables are the residuals from the regression of the original variable on the fixed effects $(\lambda_i, \lambda_j, \lambda_z).^{33}$ The results show that accounting for skill abundance does much in terms of explaining the variation in trade flows that is not accounted

\(^{32}\)That is, rather than reporting the $R^2$ increment $R^2 - R_h^2$, Table 4.10 reports

$$\left( \frac{R^2 - R_h^2}{R_h^2} \right) \times 100,$$

the percentage increase in $R^2$ from including the $h^{th}$ explanatory variable in the regression.

\(^{33}\)For example, $\hat{x}_{ijz}$ is the residual variation in trade flows that cannot be accounted for by importer, exporter, and industry fixed effects and the level of development. Therefore, I report $R^2$ for a regression purged from the variation that can be accounted for by the fixed effects. This approach is advantageous, relative to reporting $R^2$ increments for the original regression, for two reasons: 1. I am interested in determining the relative merits of different sources of comparative advantage, and as mentioned in section 2 the fixed effects account for the volume of trade, not the pattern of trade. Therefore, purging variables from these fixed effects makes sense in order that we may have a more accurate picture of the contribution of each of the other covariates in accounting for the distribution of relative exports across industries, and 2. Fixed effects alone account for most of $R^2$ in the original regression. The $R^2$ for the regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \varepsilon_{ijz}$$
Table 4.10: Accounting for the Variation in Trade Flows: $R^2$ increments

<table>
<thead>
<tr>
<th>$h^{th}$ explanatory variable</th>
<th>% Increase in $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_j \times s_z$</td>
<td>331.8</td>
</tr>
<tr>
<td>$\sigma_j \times s_z$</td>
<td>0.58</td>
</tr>
<tr>
<td>$\sigma_j \times s_z^2$</td>
<td>0.04</td>
</tr>
<tr>
<td>$K_j \times k_z$</td>
<td>7.95</td>
</tr>
<tr>
<td>$F_j \times v_z$</td>
<td>72.72</td>
</tr>
<tr>
<td>$F_j \times k_z$</td>
<td>3.26</td>
</tr>
<tr>
<td>$CE_j \times r s_z$</td>
<td>2.15</td>
</tr>
</tbody>
</table>

for by the fixed effects. In fact, it is this dependent variable that has the greatest effect on model fit from the variables under consideration. Also, notice that the $R^2$ increments suggest that residual variation in trade flows is better accounted for by factor endowments (both human and physical), than by institutional determinants of the pattern of trade.

Finally, observe that in the linear regression model the coefficient of determination can be decomposed as

$$R^2 = \sum_{h=1}^{p} \delta_h r_h,$$

where $\delta_h$ is the standardized (beta) regression coefficient of the $h^{th}$ explanatory variable and $r_h$ is the sample correlation between the dependent variable and the $h^{th}$ explanatory variable. The quantity $\delta_h r_h$ is the contribution of the $h^{th}$ explanatory variable to the explanation of the variance of the dependent variable.

Table 4.11 reports the contribution of each explanatory variable in the regression

$$\hat{x}_{ijz} = \hat{W}_{jz} \delta + \beta_0 \left( \hat{\mu_j \times s_z} \right) + \beta_1 \left( \hat{\sigma_j \times s_z} \right) + \beta_2 \left( \hat{\sigma_j \times s_z^2} \right) + \epsilon_{ijz},$$

where, once again, hatted variables denote residuals from the regression of the original variable on $(\lambda_i, \lambda_j, \lambda_z)$. It is clear from these estimates, that the distribution of is 0.9684, which implies that the combined $R^2$ increment of all determinants of the pattern of trade is in the order of 0.0003. Thus, in the original regression the presence of the fix effects mask any contribution in terms of fit made by any of the other covariates.
Table 4.11: Decomposition of $R^2$

<table>
<thead>
<tr>
<th>$h^{th}$ explanatory variable</th>
<th>Fraction of Explained Variation Accounted for</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_j \times s_z$</td>
<td>73.7%</td>
</tr>
<tr>
<td>$\sigma_j \times s_z$</td>
<td>7.4%</td>
</tr>
<tr>
<td>$\sigma_j \times s_z^2$</td>
<td>2.1%</td>
</tr>
<tr>
<td>$K_j \times k_z$</td>
<td>3.1%</td>
</tr>
<tr>
<td>$F_j \times v_z$</td>
<td>4.2%</td>
</tr>
<tr>
<td>$F_j \times k_z$</td>
<td>5.3%</td>
</tr>
<tr>
<td>$CE_j \times r s_z$</td>
<td>4.2%</td>
</tr>
</tbody>
</table>

talent accounts for more of the variation in residual trade flows than any of the other determinants of the pattern of trade. In particular, skill abundance has the highest contribution in terms of accounting for the unexplained variation in the dependent variable. These estimates also suggest that both physical and human capital play a more significant role than institutional determinants of the pattern of trade in accounting for the residual variation in trade flows. Factor endowments account for 86.3% of the explained variation in residual trade flows, while institutional endowments only account for 13.7%.

In fact, the distribution of talent alone accounts for 81% of the explained variation in residual trade flows, while the dispersion of skill accounts for 9.5%. The results discussed in this section lend further support to the hypothesis that the distribution of talent is in fact an important determinant of the pattern of trade. The results of this section are complementary to the estimates presented in Table 4.8, and taken together provide strong support to the claim that accounting for the distribution of talent, and more generally accounting for factor endowments, is important in explaining the pattern of trade, even for a subset of exporters that share similar levels of development.
4.4.4 Robustness Analysis and Alternative Specifications

I now test the sensitivity and robustness of my baseline estimates. First, I consider the robustness of my results to the presence of non-linearities in the effect of alternative sources of comparative advantage on the pattern of trade. That is, I look for evidence that might suggest that the results reported in Table 4.8 regarding the effects of the skill distribution on trade flows where, in fact, driven by unmodeled non-linearities in alternative determinants of the trade pattern. To address this issue, rather than controlling for the effect of capital endowments and institutional factors on the pattern of trade through interaction terms of the form $K_j \times k_z$, I now introduce interaction terms of the form $K_j \times g_K(k_z)$, where $g_K(\cdot)$ is a second-degree polynomial. This allows for some degree of non-linearity of the effect of alternative sources of comparative advantage on the trade pattern. Thus, the estimating equation becomes

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \mu_j \times s_z + \sigma_j \times g_\sigma(s_z) +$$

$$K_j \times g_k(k_z) + F_j \times g_f(v_z) + F_j \times g_{fk}(k_z) + CE_j \times g_c(rs_z) + \varepsilon_{ijz},$$

where the $g_i$ are second-degree polynomials.

Table 4.12 reports the results of this specification. It is confirmed that the positive, and statistically significant, estimate for the coefficient on the interaction terms $\mu_j \times s_z$ and $\sigma_j \times s_z$ remains even after controlling for possible non-linearities in the effects of capital and institutional endowments. In fact, the magnitude of the estimate for these coefficients reported in column (1) of Table 4.12 are much the same as those reported in column (3) of Table 4.8. The estimate for the coefficient on the interaction term $\sigma_j \times s_z^2$ remains statistically insignificant.

Next, I address the issue of whether $\mu$ and $\sigma$ have independent effects on the pattern of trade. Results reported in section 4.3 suggest that the mean and standard deviation of the skill distribution may be related in a systematic manner. It is then
Table 4.12: Controlling for non-linearities in alternative sources of comparative advantage

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_j \times s_z$</td>
<td>$6.18^{***}$</td>
<td>$4.31^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>$\sigma_j \times s_z$</td>
<td>$1.07^*$</td>
<td>$1.36^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.48)</td>
<td>(0.51)</td>
</tr>
<tr>
<td>$\sigma_j \times s_z^2$</td>
<td>$0.25$</td>
<td>$-0.21$</td>
</tr>
<tr>
<td></td>
<td>(0.47)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>$K_j \times k_z$</td>
<td>$-0.69$</td>
<td>$-1.33$</td>
</tr>
<tr>
<td></td>
<td>(1.11)</td>
<td>(1.12)</td>
</tr>
<tr>
<td>$K_j \times k_z^2$</td>
<td>$0.004$</td>
<td>$0.41$</td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
<td>(1.11)</td>
</tr>
<tr>
<td>$F_j \times v_z$</td>
<td>$1.34^{***}$</td>
<td>$1.39^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.31)</td>
<td>(0.31)</td>
</tr>
<tr>
<td>$F_j \times v_z^2$</td>
<td>$-1.08^{***}$</td>
<td>$-1.11^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.31)</td>
<td>(0.31)</td>
</tr>
<tr>
<td>$F_j \times k_z$</td>
<td>$-2.35^{***}$</td>
<td>$-2.34^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.52)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>$F_j \times k_z^2$</td>
<td>$2.50^{***}$</td>
<td>$2.51^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.49)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>$CE_j \times rs_z$</td>
<td>$-0.004$</td>
<td>$-0.010$</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>$CE_j \times rs_z^2$</td>
<td>$0.11$</td>
<td>$0.10$</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>$K_j \times s_z$</td>
<td>$-2.99^{***}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.80)</td>
<td></td>
</tr>
<tr>
<td>$K_j \times s_z^2$</td>
<td>$-1.84^{**}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.79)</td>
<td></td>
</tr>
</tbody>
</table>

Beta coefficients reported. Heteroskedasticity consistent standard errors in parentheses. *, **, and *** denote significance at the 5, 1, and 0.1 levels, respectively.
possible that the interaction terms $\sigma_j \times s_z$ and $\sigma_j \times s_z^2$ are simply picking up unmodeled non-linearities of the effect of skill abundance on the pattern of trade. To this end, I consider a specification in which instead of introducing the simple interaction term $\mu_j \times s_z$ to control for the effects of mean skill on trade flows, I control for the mean with the interaction $q(\mu_j) \times \tau(s_z)$, where both $q(\cdot)$ and $\tau(\cdot)$ are second-degree polynomials.

Table 4.13 reports the results from this estimation. Notice that all of the estimates for the interaction $q(\mu_j) \times \tau(s_z)$ are highly statistically significant, but more importantly, the estimate for the coefficient on the interaction $\sigma_j \times s_z$ remains positive and highly statistically significant. Furthermore, after controlling for possible non-linearities in the effect of skill abundance on the pattern of trade, the estimate on the interaction $\sigma_j \times s_z^2$ gains in statistical significance, suggesting a non-linear effect of skill diversity on trade flows after controlling for non-linear effects of skill abundance on the pattern of trade. More importantly, it is confirmed that the mean and the standard deviation of the distribution of skill have independent and statistically significant effects on the pattern of trade.

As mentioned in section 4.4.2, the baseline estimating equation is deliberately parsimonious. In what follows I consider specifications that allow for a more general effect of the mean and standard deviation of the skill distribution on trade flows. Recall that in the estimation framework the effect of $\mu$ and $\sigma$ on the dependent variable were captured through the function $g(\cdot)$, which in section 4.4.2, was modeled as the sum of three interaction terms: $\mu_j \times s_z$, $\sigma_j \times s_z$, and $\sigma_j \times s_z^2$. I now assume that the function $g(\cdot)$ is of the form $g(s_z, \mu_j, \sigma_j) = g_\mu(s_z, \mu_j) + g_\sigma(s_z, \sigma_j)$, so that I retain the additive separability of the effects of skill abundance and skill diversity on trade flows, but allow more generality than that afforded by the interaction terms of my baseline specification.

The functions $g_\mu(\cdot)$ and $g_\sigma(\cdot)$ could be estimated non-parametrically. Such an estimation would be burdensome and the exposition of such results is difficult to
### Table 4.13: Independent effect of $\mu$ and $\sigma$ on trade flows?

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_j \times s_z$</td>
<td>$-1108.70^{***}$</td>
<td>$-1125.47^{***}$</td>
</tr>
<tr>
<td></td>
<td>(187.73)</td>
<td>(186.73)</td>
</tr>
<tr>
<td>$\mu_j \times s_z^2$</td>
<td>$1319.78^{***}$</td>
<td>$1307.60^{***}$</td>
</tr>
<tr>
<td></td>
<td>(187.25)</td>
<td>(186.27)</td>
</tr>
<tr>
<td>$\mu_j^2 \times s_z$</td>
<td>$568.06^{***}$</td>
<td>$575.81^{***}$</td>
</tr>
<tr>
<td></td>
<td>(95.71)</td>
<td>(95.21)</td>
</tr>
<tr>
<td>$\mu_j^2 \times s_z^2$</td>
<td>$-667.70^{***}$</td>
<td>$-661.49^{***}$</td>
</tr>
<tr>
<td></td>
<td>(94.72)</td>
<td>(94.25)</td>
</tr>
<tr>
<td>$\sigma_j \times s_z$</td>
<td>$2.65^{***}$</td>
<td>$2.60^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.71)</td>
<td>(0.71)</td>
</tr>
<tr>
<td>$\sigma_j \times s_z^2$</td>
<td>$-1.68^*$</td>
<td>$-1.71^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.70)</td>
<td>(0.70)</td>
</tr>
<tr>
<td>$K_j \times k_z$</td>
<td>$-0.72^{***}$</td>
<td>$-0.94^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>$F_j \times v_z$</td>
<td>$0.26^{***}$</td>
<td>$0.27^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>$F_j \times k_z$</td>
<td>$0.25^{***}$</td>
<td>$0.25^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>$CE_j \times r s_z$</td>
<td>$0.10^{***}$</td>
<td>$0.08^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>$K_j \times s_z$</td>
<td>-</td>
<td>$0.98^{***}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.12)</td>
</tr>
</tbody>
</table>

Beta coefficients reported. Heteroskedasticity consistent standard errors in parentheses. *, **, and *** denote significance at the 5, 1 and 0.1 levels, respectively.
convey in an easily interpretable manner. It is for this reason that I do not proceed with a non-parametric estimation, but rather approach the problem through an exploration of the \((s, \mu)\) and \((s, \sigma)\) spaces using step functions to approximate \(g_\mu(\cdot)\) and \(g_\sigma(\cdot)\).\(^{34}\) That is, \(g_\mu\) and \(g_\sigma\) are approximated as

\[
g_\mu(s, \mu) \simeq \sum_a \sum_b \varphi_{ab} (I_{ja} \times d_{zb})
\]

\[
g_\sigma(s, \sigma) \simeq \sum_c \sum_b \zeta_{cb} (I_{jc} \times d_{zb}),
\]

where

\[
I_{jc} = \begin{cases} 
1 & \text{if exporter } j \text{ is in skill dispersion cell } c \\
0 & \text{otherwise}
\end{cases}
\]

\[
I_{ja} = \begin{cases} 
1 & \text{if exporter } j \text{ is in skill abundance cell } a \\
0 & \text{otherwise}
\end{cases}
\]

\[
d_{zb} = \begin{cases} 
1 & \text{if industry } z \text{ is in skill bin } b \\
0 & \text{otherwise},
\end{cases}
\]

Under this parametrization, the estimating equation becomes

\[
x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \sum_a \sum_b \varphi_{ab} (I_{ja} \times d_{zb}) + \sum_c \sum_b \zeta_{cb} (I_{jc} \times d_{zb}) + W_{jz} \delta + \varepsilon_{ijz},
\]

where the vector \(W_{jz}\) controls for alternative source of comparative advantage through simple interaction terms as in the previous section.

\(^{34}\)The results from this approach can be made arbitrarily close to those from non-parametric estimation since any continuous function can be arbitrarily well approximated through step functions (see Bartle [1976]). In this sense the approach here is similar in spirit to the method of sieves, discussed in Chen [2008], for the estimation of semi-nonparametric models.
The $\mu-$space is divided into three bins: low, middle, and high skill abundance. Exporters are roughly evenly distributed into these three categories. I divide the $\sigma-$space into three bins, with bin 2 containing the median dispersion, and the $s-$space into five bins, with bin 3 containing the median skill intensity.\(^{35}\) The distribution of manufacturing industries across these bins is $(10,26,26,9,5)$. Because the econometric model already includes a full set of exporter and industry fixed effects, the full set of interactions $I_{ja} \times d_{zb}$ or $I_{jc} \times d_{zb}$ cannot be included. In the former case, I decide to normalize against the lowest skill intensity bin and the lowest skill abundance cell, while in the latter I normalize against the middle skill dispersion countries and the intermediate skill-intensity industries.

Given the normalizations that I have chosen, the hypotheses that skill abundant countries possess a comparative advantage in skill intensive industries implies that we should expect to observe the following inequalities on coefficients:

$$\varphi_{25} > \varphi_{24} > \varphi_{23} > \varphi_{22} > 0$$
$$\varphi_{35} > \varphi_{34} > \varphi_{33} > \varphi_{32} > 0$$

On the other hand, the hypothesis that skill diverse countries should specialize in low and high-skill intensity sectors imply that we should expect the following inequalities on the coefficients:

$$\zeta_{11} < \zeta_{12} < 0$$
$$\zeta_{15} < \zeta_{14} < 0$$
$$\zeta_{31} > \zeta_{32} > 0$$
$$\zeta_{35} > \zeta_{34} > 0$$

\(^{35}\)Here bins are constructed based solely on the subsample of manufacturing industries.
The inequalities on the $\varphi$'s state that, since I am normalizing against lowest skill abundant countries and the lowest skill intensity sectors, the effect of moving to a higher skill abundance cell is positive, and that this effect becomes stronger as we move towards higher skill intensity bins. The inequalities on the $\zeta$'s say that, since I am normalizing against the exporters with an intermediate skill diversity and the intermediate skill intensity sectors, moving to a lower skill dispersion cell should have a negative effect, with this effect becoming more pronounced as we move towards the extremes in terms of skill intensity, while moving towards a higher skill dispersion cell should have a positive effect, with the effect increasing in magnitude as we move towards the extreme skill intensity bins.

Table 4.14 reports the estimates from this specification of the estimating equation. The estimates for $\varphi_2 = (\varphi_{22}, \varphi_{23}, \varphi_{24}, \varphi_{25})'$ respect all of the expected inequalities, except the sign restriction on $\varphi_{22}$, but this estimate is not statistically significant at conventional levels. The estimates for $\varphi_3 = (\varphi_{32}, \varphi_{33}, \varphi_{34}, \varphi_{35})'$ satisfy the string of inequalities $\varphi_{35} > \varphi_{34} > \varphi_{33} > \varphi_{32}$, but not the sign restriction on either $\varphi_{32}$ or $\varphi_{33}$, the latter estimate not being statistically significant at conventional levels. Regarding the estimates for the $\zeta$'s, the sign and inequality restrictions on $\zeta_1 = (\zeta_{11}, \zeta_{12}, \zeta_{14}, \zeta_{15})'$ are all satisfied. However, with respect to $\zeta_3 = (\zeta_{31}, \zeta_{32}, \zeta_{34}, \zeta_{35})'$ there are several violations. The sign restrictions are satisfied for $\zeta_{34}$ and $\zeta_{35}$, but not for $\zeta_{31}$ or $\zeta_{32}$. Nonetheless, all the inequality restrictions among the $\zeta$'s do hold.

The estimates from this specification provide evidence favoring the hypothesis that skill abundant countries tend to specialize in skill intensive industries. There is also evidence congruent with that from section 4.4.2, that suggests that greater skill diversity induces specialization in skill intensive industries.

The last specification that I consider in this section allows for the mean and standard deviation to affect each individual sector differentially by interacting these
Table 4.14: Approximating $g(s, \mu, \sigma)$ through step functions

determinants of the pattern of trade with industry dummies:

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \mu_j \times D_z + \sigma_j \times D_z + W_{jz} + \varepsilon_{ijz}.$$  

This specification allows for a completely non-linear effect of both of these country-level characteristics on trade flows. This specification captures the effect that $\mu$ and $\sigma$ have on the pattern of trade, without specifying the mechanism through which this occurs. That is, the estimated coefficients from this regression allow us to broach the following question: what is the effect of marginal changes in skill moments (mean or standard deviation) on the relative exports of any two manufacturing industries? However, these estimates do not give any indication as to the underlying economic mechanism driving these results. Nonetheless, these estimates do serve as an important robustness test to assess whether the first two moments of the distribution of skill are empirically significant determinants of the pattern of trade.

Because a full set of exporter and industry dummies have been included, the full set of interactions $\mu_j \times D_z$ and $\sigma_j \times D_z$ cannot be included. For $\mu_j \times D_z$ I normalized against $z = \text{NAICS}_3159$, which has the lowest average skill level for its workforce (within manufacturing industries), while for $\sigma_j \times D_z$ I normalize against $z = \text{NAICS}_3324$, which has the median skill level for its workforce (within the 76 manufacturing industries under consideration).
The first substantial result from this estimation is that out of the 75 coefficients estimated for the interaction term $\mu_j \times D_z$, 59 are statistically significant at the 10 percent level and this number only drops to 58 if I consider significance at the 5 percent level. This lends support to the claim that mean skills are an important determinant of the pattern of trade. Notice that, given that in the case $\mu_j \times D_z$ I am normalizing against the industry with the lowest skilled workforce, theory suggests that the coefficients estimated on the interactions $\mu_j \times D_z$ should all be positive and increasing as the skill intensity of the industry increases. This sign restriction is violated in only three cases, all of which are not statistically significant at conventional levels. The estimated coefficients, as a function of the skill intensity of the industry to which the coefficient belongs, are not monotonically increasing as theory would suggest. However, it is apparent from Figure 4.10 that, on average, industries with a higher skill intensity benefit relatively more from an increase in the abundance of skills.\footnote{Ordering the estimated coefficients from lowest to highest, and using this ordering to provide a ranking of industries in terms of skill intensity, produces a ranking whose correlation with $s_z$ is 0.67.} These results provide further evidence that skill abundant countries tend to export relatively more in skill intensive industries, while the non-monotonicity suggests that there might be a role for non-linear effects of skill abundance on trade flows.

For the case of the interaction term $\sigma_j \times D_z$, only 37 out of the 75 estimated coefficients are statistically significant at the 10 percent level. This lends more limited support to the claim that skill dispersion is an important determinant of the pattern of trade. Figure 4.11 shows that, on a whole, the effect of increasing skill diversity is increasing in the skill intensity of an industry. This corroborates the positive and statistically significant coefficient estimated on the interaction term $\sigma_j \times s_z$ reported in Table 4.8, and the more limited role of a non-linear effect of $\sigma$ on the determination
of the pattern of trade. The estimated coefficients on the interactions that control for alternative sources of comparative advantage remain highly statistically significant.\textsuperscript{37}

The results discussed in this subsection corroborate my earlier findings regarding the empirical relevance of the distribution of talent in the workforce as a determinant of the pattern of trade. It is found that both the mean and the standard deviation of the skill distribution are important country-level characteristics in the determination of comparative advantage. Skill abundance confers comparative advantage in skill intensive industries, while it is found that greater dispersion in the distribution of talent induces specialization in skill intensive industries as well. The evidence, however, does not find evidence in favor of the hypothesis that skill diversity confers comparative advantage in both low and high-skill intensity industries. The effect on the pattern of trade of these country level characteristics is robust to controlling for non-linearities in the effects of alternative sources of comparative advantage.

\textsuperscript{37}All estimated coefficients on these interactions are statistically significant at the 0.1 percent level. However, the puzzling result of a negative estimated coefficient for the interaction term $K_j \times k_z$ remains. This provides further evidence that the estimates found elsewhere in the literature for the effects of capital endowments on the pattern of trade are sensitive to controlling for the effect of the distribution of talent on trade flows.
4.4.5 Extensions

In section 4.4.2 it was found that, while the dispersion in skills is an important determinant of the pattern of trade, the evidence did not lend support for the kind of non-linearity implied by the theory, that is, the prediction that skill diversity confers a comparative advantage in both low-skill and high-skill intensive industries. Rather, the estimates from section 4.4.2 favored the hypothesis that differences in skill diversity, as captured by differences in the standard deviation of the skill distribution, induce specialization in skill intensive industries.

The apparent lack of evidence favoring the prediction that skill diversity implies a comparative advantage in the most extreme skill-intense industries may derive from two issues involved in the estimations presented in the previous section. First, in section 4.4.2 cross-country differences in skill diversity were summarized by differences in the standard deviation of the skill distribution. It is possible that this summary statistic provides a poor measure of the kind of underlying differences in skill diversity that are relevant for comparative advantage. In the work of Grossman and Maggi [2000] and Costinot and Vogel [2010], skill diversity is defined in terms
of either stochastic-dominance or likelihood-ratio dominance. Differences in standard
deviations do not necessarily imply either of these kind of relationships. As such, it
would seem desirable to use more of the information regarding the underlying skill
distributions to characterize differences in factor endowments and their effects on
shaping trade flows.

The second issue that may be a cause for concern is that the relevant industry
classification, skill intensity, which is proxied for by the measure $s_z$, conceals the
underlying composition of the workforce. Figure 4.12 presents the distribution of labor
cost shares for five selected 4-digit NAICS industries of similar skill intensity.\textsuperscript{38} The
fact that $s_z$ does not account for the underlying differences in the composition of an
industry’s workforce may not be a significant issue when addressing the hypothesis
that skill abundant countries should specialize in skill intensive industries, but may
well prove to be a problem when addressing the hypothesis that skill diversity confers a
comparative advantage in low and high-skill intensity industries. To see this, consider
two industries, one of which has all of its workforce comprised of average skill workers,
and another industry whose employment is divided between low and high skill workers.
These two industries would have similar values for the $s_z$ measure, yet it might well
be expected that these two industries would respond differently to changes in relative
factor prices.

In this subsection I address the former issue. As suggested above, it seems
desirable to avoid collapsing cross-country differences in skill distributions into the
summary statistics $\mu$ and $\sigma$, which may provide insufficient information about the
heterogeneity in labor supply that is relevant in shaping trade flows. Therefore, in
order that I may include more information regarding the full distribution of skills into

\textsuperscript{38} The skill intensity $s_z$ of these five industries ranges from 0.5284 to 0.5396. The distribution in
Figure 4.12 is across 10 bins, which group workers in terms of their skill relevance scores. Bin 1
contains those set of workers with the lowest skill relevance scores, and bin 10 contains those workers
with the highest skill relevance scores.
the estimating equation, I define the following (relative) composite labor inputs:

\[
Q_j^1 = \frac{\hat{F}_j(100)}{\hat{F}_j(300) - \hat{F}_j(200)}
\]

\[
Q_j^2 = \frac{\hat{F}_j(200) - \hat{F}_j(100)}{\hat{F}_j(300) - \hat{F}_j(200)}
\]

\[
Q_j^4 = \frac{\hat{F}_j(400) - \hat{F}_j(300)}{\hat{F}_j(300) - \hat{F}_j(200)}
\]

\[
Q_j^5 = \frac{1 - \hat{F}_j(400)}{\hat{F}_j(300) - \hat{F}_j(200)}
\]

where \(\hat{F}_j(\cdot)\) is the empirical cumulative distribution function of skills in country \(j\).

\[39\]

\[39\]Recall that the \(\tau\)th quantile of a random variable \(X_i\) solves

\[
F(q_{\tau}(X_i)) = \tau,
\]

where \(F(\cdot)\) is the cdf of \(X\). This implies that a fraction \(\tau\) of the observations are below \(q_{\tau}\), while a fraction \(1 - \tau\) of the observations are above \(q_{\tau}\). The distribution of \(X\) is fully characterized by the set of \(q_{\tau}(X_i)\) for \(\tau \in [0, 1]\).
Here, rather than dividing the labor pool into two classes of workers, skilled and unskilled as is common elsewhere in the literature\(^{40}\), I divide the labor pool into 5 groups of workers, and with the \(Q_j^k\)'s measure the relative endowment of these groups with respect to the middle group (i.e. those workers with a skill level between 200 and 300, which is the group that contains the mean and median skill level in all countries). Countries that are skill diverse should be expected to have relatively high values of \(Q^1\) and \(Q^5\), which are the groups with the most extreme skilled workers, while countries that are not skill diverse should be expected to have relatively higher values of \(Q^2\) and \(Q^4\), which are those workers with skill levels closer to the mean skill level. Finally, let \(q_j^k = \ln(e + Q_j^k)\) for \(k = 1, 2, 4, 5\).\(^{41}\) Table 4.15 displays the cross-country variation in these relative factor endowments.

Correspondingly, I divide occupations into 5 groups according to their skill relevance scores and define factor intensities in industry \(z\) as

\[
q_z^k = \omega_{kz} \times \left( \frac{\text{Total Payroll}_z}{\text{Value Added}_z} \right)
\]

where \(\omega_{kz}\) is the employment share in industry \(z\) of occupations in group \(k = 1, 2, 3, 4, 5\).

I now consider the following estimating equation

\[
x_{ijz} = \lambda_i + \lambda_j + \lambda_z + W_{jz} \delta + \sum_k \beta_k (q_j^k \times q_z^k) + \varepsilon_{ijz}.
\]

\(^{40}\)One may consider the case in which the labor pool is divided into low and high skill workers as the case in which we define the relative supply of high-skilled workers

\[
\frac{L_s}{L_u} = \frac{1 - \hat{F}(\tau)}{F(\tau)}
\]

for some \(\tau\) in the support of the skill distribution.

\(^{41}\)Notice that \(q_j^k\) is being normalized to unity for those cases in which \(Q_j^k = 0\).
<table>
<thead>
<tr>
<th>Country</th>
<th>$q^1$</th>
<th>$q^2$</th>
<th>$q^4$</th>
<th>$q^5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>1.002</td>
<td>1.041</td>
<td>1.294</td>
<td>1.001</td>
</tr>
<tr>
<td>Canada</td>
<td>1.011</td>
<td>1.108</td>
<td>1.178</td>
<td>1.002</td>
</tr>
<tr>
<td>Chile</td>
<td>1.026</td>
<td>1.220</td>
<td>1.027</td>
<td>1.000</td>
</tr>
<tr>
<td>Czech Rep.</td>
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<td>1.026</td>
<td>1.263</td>
<td>1.001</td>
</tr>
<tr>
<td>Denmark</td>
<td>1.000</td>
<td>1.018</td>
<td>1.289</td>
<td>1.000</td>
</tr>
<tr>
<td>Finland</td>
<td>1.001</td>
<td>1.035</td>
<td>1.295</td>
<td>1.001</td>
</tr>
<tr>
<td>Germany</td>
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<td>1.020</td>
<td>1.199</td>
<td>1.000</td>
</tr>
<tr>
<td>Hungary</td>
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<td>1.076</td>
<td>1.000</td>
</tr>
<tr>
<td>Ireland</td>
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<td>1.076</td>
<td>1.150</td>
<td>1.001</td>
</tr>
<tr>
<td>Italy</td>
<td>1.009</td>
<td>1.083</td>
<td>1.116</td>
<td>1.000</td>
</tr>
<tr>
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<td>1.001</td>
<td>1.030</td>
<td>1.242</td>
<td>1.000</td>
</tr>
<tr>
<td>New Zealand</td>
<td>1.002</td>
<td>1.045</td>
<td>1.208</td>
<td>1.001</td>
</tr>
<tr>
<td>Norway</td>
<td>1.001</td>
<td>1.034</td>
<td>1.381</td>
<td>1.001</td>
</tr>
<tr>
<td>Poland</td>
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<td>1.139</td>
<td>1.069</td>
<td>1.000</td>
</tr>
<tr>
<td>Slovenia</td>
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<td>1.078</td>
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<td>1.364</td>
<td>1.005</td>
</tr>
<tr>
<td>Switzerland</td>
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<td>1.205</td>
<td>1.000</td>
</tr>
<tr>
<td>UK</td>
<td>1.011</td>
<td>1.075</td>
<td>1.196</td>
<td>1.001</td>
</tr>
<tr>
<td>USA</td>
<td>1.014</td>
<td>1.124</td>
<td>1.207</td>
<td>1.002</td>
</tr>
</tbody>
</table>

Table 4.15: Cross-Country Variation in Composite Labor Inputs

The results from this estimation may prove useful in understanding how the distribution of talent shapes trade flows to the extent that: (a) workers with a skill level in group $[0, 100]$, roughly, sort into the set of occupations with the lowest skill relevance scores, workers with a skill level in group $[100, 200]$ sort into the set of occupations in group two with the second lowest range of skill relevance scores, and so on; and (b) these aggregate labor inputs are complementary in production, rather than substitutes.

As in section 4.4.2, I proceed by estimating first the short regression

$$x_{ijz} = \lambda_i + \lambda_j + \lambda_z + \sum_k \beta_k (q^k_j \times q^k_z) + \epsilon_{ijz},$$

and then consider a series of long-regressions to control for alternative determinants of the pattern of trade. Results are reported in Table 4.16.
Column (1) in Table 4.16 reports the results for the short-regression. Consistent with the predictions of standard factor proportions theory, the estimate for $\beta = (\beta_1, \beta_2, \beta_4, \beta_5)'$ is positive, and except for $\beta_2$, highly statistically significant. Next I control for institutional determinants of the pattern of trade, and for capital endowments as a source of comparative advantage; the results are reported in column (2) of Table 4.16. The estimates for $\beta_1$, $\beta_2$, and $\beta_5$ are all positive and statistically significant. The estimate for $\beta_4$ is negative, but not statistically significant at conventional levels. Finally, I control for the effect of the level of development on trade flows, and for the possibility that capital abundance, through its effect on factor prices, affects specialization differentially across industries varying in terms of the factor intensities of the composite labor inputs. The results of the estimation with these additional controls are presented in column (3) of Table 4.16. The estimates for $\beta_1$, $\beta_2$, and $\beta_5$ remain positive and highly statistically significant. Notice however, that the estimate for $\beta_4$ is negative, and statistically different from zero.

The estimates presented in Table 4.16 attest to the importance of relative factor endowments in shaping trade flows. In particular, they point to the importance of taking into account the heterogeneity in the labor input when accounting for the determinants of comparative advantage. Because standardized coefficients are reported, they can be compared directly in terms of their impact on the dependent variable. Notice that within this group of exporters, a one standard deviation change in either $q_j^1 \times q_z^1$ or $q_j^5 \times q_z^5$ has a more substantial impact on trade flows than a one standard deviation change in any of the other covariates. In fact, the estimates from column (3) imply that a simultaneous one standard deviation change in the covariates that control for alternative determinants of comparative advantage results in a change of 2.153 standard deviations of the dependent variable; notice that a one standard deviation change in either $q_j^1 \times q_z^1$ or $q_j^5 \times q_z^5$ results in a more significant change, in terms of standard deviations, of the dependent variable.
<table>
<thead>
<tr>
<th>Explanatory Variable</th>
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<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_j \times q_z^1$</td>
<td>2.47***</td>
<td>5.02***</td>
<td>3.89***</td>
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<tr>
<td></td>
<td>(0.36)</td>
<td>(0.42)</td>
<td>(0.48)</td>
</tr>
<tr>
<td>$q_j^2 \times q_z^2$</td>
<td>0.04</td>
<td>0.32***</td>
<td>0.45***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>$q_j^4 \times q_z^4$</td>
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<td>-0.001</td>
<td>-0.412***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>$q_j^5 \times q_z^5$</td>
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<td>24.89***</td>
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</tr>
<tr>
<td></td>
<td>(1.94)</td>
<td>(1.97)</td>
<td>(1.86)</td>
</tr>
<tr>
<td>$K_j \times k_z$</td>
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<td>(0.99)</td>
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<tr>
<td>$F_j \times v_z$</td>
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<td>$F_j \times k_z$</td>
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<td>0.59***</td>
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<td>(0.05)</td>
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<td>$CE_j \times r_s_z$</td>
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<td>$K_j \times q_z^1$</td>
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<td>-</td>
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<td>-</td>
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<td>$K_j \times q_z^5$</td>
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<td>0.97</td>
</tr>
<tr>
<td>No.Observations</td>
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<td>98703</td>
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</tr>
</tbody>
</table>

Beta coefficients reported. Heteroskedasticity robust standard errors in parentheses. *, **, *** denote significance at the 10, 5, 1 and 0.1 percent levels, respectively.

Table 4.16: The Determinants of Comparative Advantage
These results lend support to the hypothesis that accounting for the heterogeneity in the labor input is important in assessing the determination of trade flows. In particular, they offer evidence in favor of the hypothesis that relative factor differences at the low and high end of the skill distribution are important in accounting for the pattern of trade among exporters at a similar level of development.

4.5 Conclusions

What goods do countries trade? This is a central question in many theories of international trade, and my results have something to say in this regard. In this chapter I have tested whether the distribution of talent in the workforce is a source of comparative advantage and found that both the mean and standard deviation of the skill distribution are economically, and statistically, significant determinants of the pattern of trade. In particular, my results present strong evidence to support the hypothesis that skill abundant countries possess a comparative advantage in skill intensive sectors.

The data also provides strong evidence that skill diverse countries, as measured through the standard deviation of the skill distribution, tend to specialize in skill intensive industries. However, the hypothesis that skill diversity confers comparative advantage in low and high-skill intensity industries finds weak support in the data. It is possible that I am not able to accurately identify the comparative advantage prediction related to this higher moment of the skill distribution because there is insufficient variation along this dimension for the group of exporters under consideration.

A cross-country comparison of the skill distributions finds that when skill abundance and skill dispersion are defined in terms of stochastic dominance rather than by comparing summary statistics of the distributions, out of the 171 possible pairwise comparisons of skill distributions only 43 correspond to cases in which we can say
that one distribution is more skill diverse than the other. Thus, for the group of
exporters under consideration, most cross-country differences in skill distributions
are characterized by differences in skill abundance, rather than by differences in skill
diversity. This may help shed some light as to why I find such a strong effect for
the mean skill level on the pattern of trade, but a more limited role for the standard
deviation.

A possible limitation of the results presented in section 4 is that cross-country
differences in skill distributions are not adequately captured through differences in
the mean and standard deviation of these distributions. That is, the country char-
acteristic of interest, which is the distribution of skill in the population, cannot be
meaningfully collapsed to a few summary statistics in order to properly assess compar-
ative advantage predictions. The estimates presented in section 5 speak to this effect
and are indicative of the importance of including more detailed information regarding
the full extent of the underlying heterogeneity in skills to accurately determine the
importance of the distribution of talent in the population in shaping trade flows. Once
this is done, the evidence is more favorable the comparative advantage prediction that
suggests that countries that are skill diverse, and thus relatively abundant in both
low and high-skill workers, will export relatively more in low and high-skill intensity
sectors.

According to my estimates, factor proportions theory is still clearly favored as
the most successful theory explaining the pattern of trade, once it is recognized that
labor is a highly heterogeneous input in production. The distribution of talent has
a more significant impact on trade flows, and explains more of the pattern of trade,
than capital endowments and institutional determinants of comparative advantage
for the set of exporters under consideration.
Bibliography


Appendix
4.A Other Data Sources

Data on total exports from exporter $j$ to importer $i$ in industry $z$ are taken from the World Trade Flows Database 1962-2000 (see Feenstra et. al [2005]). The data are from the period 1996-2000 and are measured in thousands of U.S. dollars. The data is originally classified according to the 4-digit SITC Rev. 2 system. I map the data to the 4-digit NAICS 1997 classification using the SITC to NAICS concordance available at the NBER website.\footnote{http://www.nber.org/lipsey/sitc22naics97/}

Capital endowment data is taken from the Penn World Tables (PWT). The relevant variable is KAPW, which measures “total capital stock per worker”. Data is for the period 1997-2000 and it is measured in 2000 prices in international dollars. The international dollar is a currency created for the PWT data, where an international dollar has the purchasing power over all of GDP (but not the components) of a US dollar in current prices of the benchmark year. KAPW is not available for the the Czech Republic or Slovenia.\footnote{OECD does not provide any estimates for the capital endowment of the these two countries either.} Real per capita GDP data is also taken from PWT. The relevant variable is CGDP and the data is for the period 1998-2000.

The measure of contract enforcement $CE_j$ is from Nunn [2007]. The contract enforcement variable is an index that ranges from 0 to 1, with a higher number indicating greater contract enforcement. This variable is derived from a “rule of law” index that measures the extent to which agents have confidence in and abide by the rules of society.

The measure of labor market flexibility $F_j$ is from Cuñat and Melitz [2010]. This variable is an index that ranges from 0 to 100, with a higher number indicating a greater extent of labor market flexibility. The measure is derived from a summary index produced by the World Bank that combines different dimensions of labor market
rigidity such as hiring costs, firing costs, and restriction on changing the number of working hours.

Contract intensity (or relationship-specificity) \( r s_z \) is the variable \( z^{rs1} \) from Nunn [2007], which measures the proportion of an industry’s inputs, weighted by value, that require relationship-specific investments. Nunn’s variable is classified according to the I-O classification. I map the data to the 4-digit NAICS classification using the concordance available from the BEA. The 4-digit NAICS contract intensity used is constructed as \( z_k = \sum \omega_i z_i \), where the sum is over the set of I-O industries that map into a 4-digit NAICS industry, and \( \omega_i \equiv u_i / \sum u_j \) where \( u_i \) is the total value of inputs used in \( i \).

The industry volatility variable \( v_z \) is the variable \( VOL_s \) from Cuñat and Melitz [2010]. This variable measures industry volatility as the standard deviation of the growth rate of firm sales. This variable is classified according to the US SIC classification, and I map this data into the 4-digit NAICS classification using the concordance available from the BEA. The variable \( v_z \) corresponds to the average volatility of the I-O industries that map into a 6-digit NAICS industry encompassed by the 4-digit industry.

Data on capital intensities across industries are from NBER-CES Manufacturing Industry Database (see Bartelsman et. al. [2009]). Capital intensity \( k_z \) is measured as

\[
1 - \frac{\text{Total Payroll}}{\text{Value Added}}
\]

for industry \( z \) in the United States in the year 2000. The original data is classified according to the NAICS 1997 classification, but reported at the more disaggregated 6-digit level. I aggregate 6-digit categories up to the 4-digit level.

The construction of the variable \( s_z \), which measures skill intensity at the industry level, is described in section 3. Construction of this variable makes use of employment and wage data from the National Employment Matrix, available from the Bureau of
Labor Statistics, and the O*NET v.14 database on occupational descriptors. The O*NET database contains several hundred variables that represent descriptors of work and worker characteristics, including skill requirements for over 800 SOC occupations. For several of these occupational descriptors the O*NET database reports importance and level ratings of these descriptors for a particular occupation. The importance rating indicates the degree of importance a particular descriptor is to the occupation. The possible ratings range from “Not Important” (1) to “Extremely Important” (5). The level rating indicates the degree, or point along a continuum, to which a particular descriptor is required or needed to perform the occupation\textsuperscript{44}. These ratings are derived, primarily, from the ratings of job incumbents and to a lesser degree from the ratings provided by occupational analysts. Because different descriptors utilize different rating scales, all ratings are reported as standardized scores:

\[ r = \left( \frac{O - L}{H - L} \right) \times 100 \]

where

\begin{align*}
O & = \text{original score on the rating scale} \\
L & = \text{lowest possible score on the rating scale} \\
H & = \text{highest possible score on the rating scale}.
\end{align*}

The National Employment Matrix provides detailed employment information for 4-digit NAICS 1997 industries. This matrix contains employment shares (and levels) for SOC occupations, as well as average industry wage data for these occupations.

\textsuperscript{44}The level rating for an item is identified as “not relevant” for a particular occupation when a majority (75\% or more) of the incumbents or occupational analysts rate the corresponding importance item as “not important”.
Tables 4.17 and 4.18 present summary statistics for the industry-level and country-level characteristics of interest. Those summary statistics are calculated based on the subsample of industries and exporters for which there is data available for all variables.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Coefficient Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skill Intensity</td>
<td>0.57</td>
<td>0.10</td>
<td>0.37</td>
<td>0.85</td>
<td>0.18</td>
</tr>
<tr>
<td>Capital Intensity</td>
<td>4.95</td>
<td>0.82</td>
<td>3.03</td>
<td>7.26</td>
<td>0.17</td>
</tr>
<tr>
<td>Volatility</td>
<td>0.18</td>
<td>0.04</td>
<td>0.11</td>
<td>0.29</td>
<td>0.21</td>
</tr>
<tr>
<td>Rel. Specificity</td>
<td>0.51</td>
<td>0.21</td>
<td>0.06</td>
<td>0.94</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Table 4.17: Industry-level Characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Coefficient Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Skill</td>
<td>5.59</td>
<td>0.10</td>
<td>5.34</td>
<td>5.70</td>
<td>0.02</td>
</tr>
<tr>
<td>Std. Deviation Skill</td>
<td>3.98</td>
<td>0.16</td>
<td>3.70</td>
<td>4.26</td>
<td>0.04</td>
</tr>
<tr>
<td>Capital Stock</td>
<td>11.60</td>
<td>0.42</td>
<td>10.59</td>
<td>12.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Labor Market Flexibility</td>
<td>4.25</td>
<td>0.23</td>
<td>3.81</td>
<td>4.57</td>
<td>0.05</td>
</tr>
<tr>
<td>Contract Enforcement</td>
<td>0.84</td>
<td>0.11</td>
<td>0.61</td>
<td>0.97</td>
<td>0.12</td>
</tr>
<tr>
<td>log(GDP per capita)</td>
<td>9.96</td>
<td>0.38</td>
<td>9.11</td>
<td>10.41</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Table 4.18: Country-level Characteristics
Chapter 5

Conclusions

The research presented in this volume focused on the utilization of econometric and quantitative methods, together with rich data sets, to study issues in applied international trade. This dissertation contributes to the empirical trade literature along three separate dimensions. In chapter two I contribute to the empirical trade literature that uses firm-level data sets to provide further support for theories that emphasize the role that the decisions of profit-maximizing firms have on mediating a nation’s exports. It is shown that this theories can account for cross-sectional facts regarding the distribution of exports across firms and destinations, but that their dynamic counterparts fare less well when contrasted against the data. In particular, the dynamics for new export entrants implied by these models are at odds with what is observed in the data. In addition, I provide a more detailed account of the dynamics of new export entrants than what is currently available in the literature by documenting the internationalization process of firms along both the extensive and intensive margins of trade. The patterns of gradual expansion suggest that there are frictions that inhibit new export entrants from achieving their long-term scale of operation in export markets upon entry. In chapter three I use detailed transaction data from Mexican exporters to build and estimate a micro founded model of export
supply featuring self-discovery. The estimated model accounts well for key features of the observed dynamics of new export entrants, which were documented in chapter two. The model and my estimates allow me to quantify the role that learning about foreign markets plays in the export supply decision of new exporters. I find that the discovery stage in the export market lasts for approximately four years, that the rewards of self-discovery take the form of higher ex-ante probabilities of serving the foreign market and higher export premia, and that temporary shocks to the profitability of serving the foreign market can have long-lived effects on total exports. Finally, in chapter four I use data on trade flows together with test scores from the International Adult Literacy Survey (IALS) -to construct a novel measure of the distribution of talent in the population- to assess the role that worker heterogeneity has in shaping the pattern of trade. My estimates show that the distribution of skills explains more of the pattern of trade than countries’ endowment of capital and institutional features combined, at least for the set of exporters under consideration.