

Comparative Advantage, Firm Heterogeneity, and Selection of Exporters

Isao Kamata[†]

University of Wisconsin–Madison

This version: February 1, 2010

Abstract

This paper investigates how the fraction of exporting firms among domestic firms in a country differs across industries, depending on a country's comparative advantage. A model, which extends work by Melitz (2003) and Bernard, Redding and Schott (2007), describes an economy that comprises two countries asymmetrically endowed with two production factors, many industries differing in the relative intensity of the two production factors, and a continuum of firms differing in productivity. The model predicts a comparative advantage-driven pattern of the exporter selection: the fractions of exporting firms among all domestic firms are ranked according to the order of industries' relative intensities of a production factor with which the country is relatively well-endowed. This quasi-Heckscher-Ohlin prediction about the exporter fraction is empirically tested using data from the manufacturing censuses of Chile, Colombia, India, and the United States. The result of the analysis shows that the correlation between the exporter fractions and industry skill intensities is larger, or more positive, for a country with higher skilled-labor abundance, which confirms the theoretical prediction and demonstrates the role of comparative advantage in exporter selection.

JEL classification: F11, F12, L11

Keywords: comparative advantage, Heckscher-Ohlin, exporter selection, productivity heterogeneity

[†] Robert M. La Follette School of Public Affairs, the University of Wisconsin–Madison (e-mail: ikamata@lafollette.wisc.edu). I would like to thank Alan Deardorff, Juan Carlos Hallak, Jagadeesh Sivadasan, and Bob Stern for extensive discussion and helpful suggestions. I also thank Peter Morrow and participants in seminars at Bank of Japan Institute for Monetary and Economic Studies, Clark University, Ryerson University, Syracuse University, the University of Michigan, the University of Pittsburgh, and the University of Wisconsin for valuable comments. In addition, I would like to acknowledge the support from Jim Levinsohn and Jim Tybout by permitting and providing me with access to the Chilean and Colombian datasets. All errors are my own.

1. Introduction

Some firms export but others do not. Since Bernard and Jensen (1995) pointed this out for the United States, this fact has been confirmed for various countries and industries. The fraction of exporters among domestic firms in a country, however, varies widely across industries. For instance, as shown in Table 1, in the United States, 49% of firms in the electric equipment industry export, while only 13% export in the stone, clay, and glass products industry,¹ even though the total number of firms is almost the same in the two industries. A difference in the fraction of exporters among domestic firms can also be seen across countries in the same industry. For example, 54% of Indian firms in the apparel industry are exporters, while only 12% of American firms in this same industry export. At the same time, the share of exporters in the electric equipment industry is 17% in India, but 49% in the United States.² These examples illustrate that cross-industry variation in exporter fraction (i.e., in what industries firms are more likely to export) does not follow the same pattern for all countries.

This difference in the likelihood of domestic firms being exporters in different industries and countries indicates that country-based and industry-based influences must be involved. These affect individual firms' decision to export or not. To date, however, empirical studies have focused on firm-level determinants generating heterogeneity in export behavior among firms. Little work has investigated how the fraction of exporters among domestic firms differs across industries and countries and what generates these differences. This paper explains this cross-industry and cross-country variation in the exporter fraction from the

¹ The data are for the year 1992. In 1992, the share of exporters in all firms was 22% in the manufacturing industry in total. Therefore, the exporter share in the electric equipment industry (U.S. Standard Industry Classification code 36) was more than the double of the exporter share in all the manufacturing sectors, while the share in the stone, clay, and glass products industry (U.S. SIC code 32) was about 60% of that in the whole manufacturing industry.

² The data for India are for the fiscal year 1997/98 (April 1997-March 1998). In this year, the share of exporters in all the manufacturing firms was 14% in India.

perspective of comparative advantage, in particular comparative advantage in terms of factor proportion. Although other potential country-specific or industry-specific determinants of the selection of exporters can be considered, the empirical analysis in this paper shows that the observed patterns of the exporter fraction can be well explained by comparative advantage, or countries' relative factor abundance and industries' relative factor intensity.

The influence of factor proportion-based comparative advantage on difference in firm-level export decision has been theoretically examined by Bernard, Redding and Schott (2007). They incorporate the model by Melitz (2003), which has provided a theoretical benchmark explaining the empirical regularity of self-selection of exporters (i.e., firms that are the most productive in a domestic market become exporters), into a two-country, two-factor and two-industry framework. To derive a prediction describing an empirical relationship between the exporter fraction and factor proportion, this paper extends the model by Bernard, Redding and Schott to a multi-industry framework. That is, this paper considers an economy that comprises two countries differing in the relative abundance of two production factors (skilled and unskilled labor) and a large number of industries differing in the relative intensity of the two production factors. In these two countries each industry is populated with a continuum of firms differing in total factor productivity. Two threshold levels of firms' productivity, one of which divides domestic producers from "exiters" and the other divides these domestic producers into exporters and non-exporters, are created through monopolistic competition and costly international trade. However, the impact of international trade on the two productivity cutoffs is asymmetric across industries, due to the difference in factor proportion. Keener competition among firms seeking larger potential export profits raises the domestic-production productivity cutoff more in comparative-advantage industries, while the cutoff for

exporting is relatively lower in these industries due to the comparative advantage over foreign competitors. This impact of trade on the two productivity cutoffs is more pronounced with the strength of comparative advantage; as a result, the “gap” between the two productivity cutoffs, which is measured as the ratio of the export cutoff to the domestic-production cutoff, is the largest in the industry with the lowest relative intensity of the factor with which the country is relatively well-endowed, and the smallest in the industry with the highest relative intensity of that factor. This ratio of the two productivity cutoffs determines the ex post fraction of exporters among domestic producers (the smaller the gap, the larger the fraction). Therefore, if all other conditions are equal between countries and among industries, in the relatively more skilled-labor abundant country, the exporter fraction rises with an industry’s relative skilled-labor intensity, and vice versa.

Empirically, this theoretical prediction is examined as a correlation between the fraction of exporters among domestic firms and the relative skill intensity of industries. That is, the correlation should be larger (i.e., more positive or less negative) for a country with higher relative skilled-labor abundance, compared to less skilled-labor abundant countries. This empirical prediction is tested using data from the manufacturing censuses of Chile, Colombia, India, and the United States. These four countries represent a variety of country groups in terms of relative skill abundance. The results of estimation for individual countries present that the correlation between the exporter fraction and industry skill intensity in fact differs across countries, and the values of correlation coefficients estimated for the four countries follow the order of the countries’ skilled-labor abundance; i.e., the correlation is of the largest positive for the United States, and declines for Chile, Colombia, and towards a negative value for India. This relationship between the countries’ skill abundance and the

correlation between the exporter fraction and industry skill intensity is more formally tested using pooled data for these four countries and 17 manufacturing industries classified according to the two-digit U.S. Standard Industrial Classification (SIC). The result confirms that the correlation between the exporter fraction and industry skill intensity rises (toward positive) with the relative skill abundance of a country.³ This result is robust across alternative measures of country skill abundance and industry skill intensity. The estimation using relative factor price (the ratio of skilled-labor wage to unskilled-labor wage) as another measure of comparative advantage also supports the quasi-Heckscher-Ohlin prediction about the exporter fraction.

The finding of quasi-Heckscher-Ohlin effect on the exporter fraction in this paper has an additional implication for international trade. In the representative- (or symmetric-)firm framework by Romalis (2004), the industrial composition of a country's exports in terms of the number of firms (or product varieties) is symmetric to the industrial composition of the country's domestic production.⁴ In other words, a country has larger shares of world total exporters in comparative-advantage industries because the country has larger shares of world total producers. This is not necessarily the case in the current model. Since a country's comparative advantage also affects the mechanism of exporter selection, it may be that despite a small share of producers in the world, a country's share of exporters is large in a comparative-advantage industry. Some examples are found in Table 1. In the apparel industry, for instance, the number of Indian domestic firms is the double of the number of Chilean firms; however, the number of Indian exporters is eight-fold that of Chilean exporters in that

³ This result can also be interpreted from the cross-country point of view in the following way: the correlation between the exporter fraction and country relative skill abundance is larger, or more positive, in a more skill-intensive industry.

⁴ More accurately, the number of domestic producers is the same as the number of exporters since the model does not have the mechanism of the selection of exporters (all domestic firms export).

industry. That is, the effect of comparative advantage on the number of firms (or the extensive margin) can be magnified through exporter selection.⁵

This study adds to the literature in two ways. First, this paper is the first to empirically investigate cross-country and cross-industry asymmetry in the (self-)selection of exporters. Since Bernard and Jensen (1995), a great number of empirical studies have investigated differences between exporters and non-exporters focusing on a single country, some of which further narrow their focuses on a single industry (see Greenaway and Kneller (2007), Lopez (2005), and Wagner (2007) that are extensive surveys of this literature). This paper takes one step back in focus and addresses the issue of firm-level heterogeneity in export behavior from a cross-country and cross-industry perspective. In addition, this paper adds to few theoretical studies on firm-level heterogeneity in export decision that takes into account asymmetry of countries such as Falvey et al. (2004) and Melitz and Ottaviano (2008), or of both countries and industries such as Bernard, Redding and Schott (2007).

Secondly, this paper empirically demonstrates the effect of the factor proportion-based comparative advantage on another dimension of international trade, i.e., the fraction of exporting firms among domestic firms. The Heckscher-Ohlin framework, or the factor proportion theory, has been empirically tested for the specialization patterns of countries' net trade flows (e.g., Baldwin (1971), Harkness (1978), and Stern and Maskus (1981); also see the survey by Deardorff (1984)), production (Harrigan and Zakrajsek (2000) and Fitzgerald

⁵ The effect of comparative advantage can be even more magnified in the volume of exports. For example, in the apparel industry the volume of Indian exports is more than 50 times greater than the volume of Chilean exports. (In contrast, in Romalis' model the share in the volume of exports is also symmetric to the share in the number of firms.) Although this paper does not directly address this issue, the present model has the potential for explaining this magnification of the effect of comparative advantage in export volume as a result of differences in relative productivity among exporters in different industries.

and Hallak (2004)), and the relative volume of trade (Romalis, 2004).⁶ Kamata and Yang (2007) demonstrates that the factor-proportion framework also provides a prediction about the relative product variety in countries' exports. This paper demonstrates that the (quasi-) Heckscher-Ohlin framework also explains the patterns of the exporter fractions. In addition, this paper extends the model by Bernard, Redding & Schott to a multi-industry framework, which is analogous to the work by Dornbusch, Fischer and Samuelson (1980) that extends the standard Heckscher-Ohlin model with perfect competition, and Romalis' (2004) extension of the monopolistic competition model by Helpman and Krugman (1985).

The organization of the rest of the paper is as follows. The next section presents the economic model and derives the prediction of the cross-industry pattern of exporter selection. The third section describes the data that are used in the empirical analysis, which is demonstrated in Section 4. The concluding section discusses the results and implications.

2. The Model

This paper adopts the model by Bernard, Redding and Schott (2007) and extends it to the framework of two countries, two factors and multiple industries. The modeled economy comprises two countries, Home (H) and Foreign (F); two factors, skilled labor (S) and unskilled labor (U); and $N (>2)$ industries. Within each industry there is a continuum of firms that are heterogeneous in productivity. Countries differ in factor endowments: Home is relatively abundant in skilled labor, and Foreign is relatively abundant in unskilled labor; i.e.,

$$\frac{\bar{S}^H}{\bar{U}^H} > \frac{\bar{S}^F}{\bar{U}^F} \text{ where } \bar{S}^H (\bar{U}^H) \text{ and } \bar{S}^F (\bar{U}^F) \text{ denote the total inelastic supply of (un)skilled}$$

⁶ Another large branch of the literature is empirical tests of the Heckscher-Ohlin-Vanek model of the factor contents of trade.

labor in Home and Foreign, respectively.

Consumption

The representative consumer possesses Cobb-Douglas preferences over $N > 2$ industries that are described by the following first-tier utility function:

$$U = C_1^{\alpha_1} C_2^{\alpha_2} \dots C_N^{\alpha_N}, \quad \sum_{i=1}^N \alpha_i = 1 \quad (1)$$

where C_i represents the consumption index for Industry $i = 1, \dots, N$. The representative consumer consumes all the available product varieties within each industry, and the industry-wise consumption index C_i takes the following CES (or Dixit-Stiglitz) form:

$$C_i = \left[\int_{\omega \in \Omega_i} q_{\omega}^{\rho} d\omega \right]^{\frac{1}{\rho}} \quad (2)$$

where ω indexes product varieties within an industry, Ω_i denotes a set of available varieties in Industry i , and q_{ω} represents the quantity of each variety consumed. Accordingly, the price index P_i over individual varieties of products in Industry i is defined as:

$$P_i = \left[\int_{\omega \in \Omega_i} p_{i,\omega}^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \quad (3)$$

where $\sigma = \frac{1}{1-\rho} > 1$ is the constant elasticity of substitution across varieties.

Production

Each firm produces a unique variety of products. A firm's total cost of production is the sum of fixed costs and variable costs. The fixed costs are the same for all firms in an

industry within a country,⁷ but the variable costs vary across firms according to the difference in their productivity $\phi \in (0, \infty)$. The cost function for Firm ω in Industry i in each country is:

$$\begin{aligned}\Gamma_{i,\omega}^H &= \left[f_i + \frac{q_{i,\omega}}{\phi_{i,\omega}} \right] \cdot (s^H)^{\beta_i} (w^H)^{1-\beta_i} \\ \Gamma_{i,\omega}^F &= \left[f_i + \frac{q_{i,\omega}}{\phi_{i,\omega}} \right] \cdot (s^F)^{\beta_i} (w^F)^{1-\beta_i}\end{aligned}\tag{4}$$

where s is the wage for skilled labor, w is the wage for unskilled labor, and the superscripts H and F denote Home and Foreign, respectively. The industries are ranked according to the Cobb-Douglas cost share of skilled labor (β_i), such that the industry indexed with a large number for i has a larger skilled-labor cost share: $0 < \beta_1 < \beta_2 \dots < \beta_{N-1} < \beta_N < 1$. Within an industry, the cost share of each factor does not differ across countries or across firms. Note that the factor intensity of Industry i is also ranked using the rank of β_i ,⁸ and thus β_i can be regarded as an indirect index of industry factor intensity.

In what follows, I present equations and expressions for Home, unless otherwise noted. The equations for Foreign are symmetric.

With the Dixit-Stiglitz preferences, the optimal price of a firm's product variety equals a constant markup ($1/\rho$) over the marginal cost of production.

$$p_{i,\omega}^H(\phi_{i,\omega}) = \frac{(s^H)^{\beta_i} (w^H)^{1-\beta_i}}{\rho \phi_{i,\omega}}\tag{5}$$

Revenue of each firm from its domestic (Home) sales thus takes the following form:

⁷ As shown in Equation (4), since the fixed costs also depend on the prices of two production factors, the fixed costs is in general different between the two countries due to the difference in factor prices.

⁸ Since the equilibrium relative factor intensity in each industry is

$$\frac{S_i}{S_i + U_i} = \frac{\beta_i}{\beta_i + (1 - \beta_i) \cdot (s/w)},$$

and therefore for any relative wage $s/w > 0$, $S_i/(S_i + U_i)$ is larger for a larger β_i .

$$r_{i,\omega}^H(\phi_{i,\omega}) = \alpha_i Y^H \left(\frac{(s^H)^{\beta_i} (w^H)^{1-\beta_i}}{\rho \phi_{i,\omega} P_i^H} \right)^{1-\sigma} \quad (6)$$

where Y^H is the total national income of Home. The profit of each firm is equal to revenue minus production costs, which is as follows:

$$\pi_{i,\omega}^H(\phi_{i,\omega}) = \frac{r_{i,\omega}^H(\phi_{i,\omega})}{\sigma} - f_i (s^H)^{\beta_i} (w^H)^{1-\beta_i} \quad (7)$$

Entry and Equilibrium in Autarky

To describe the general idea with simpler expressions, I first describe the equilibrium in an autarkic economy. To enter the domestic market, each firm incurs a sunk entry cost. Firms discover their productivity after the entry. The productivity parameter ϕ is randomly drawn from a distribution $G(\phi)$, which is common across countries. The entry cost also depends upon the prices of the two input factors, and takes the following form:

$$f_{ei} (s^H)^{\beta_i} (w^H)^{1-\beta_i}, \quad f_{ei} > 0 \quad (8)$$

In other words, the Cobb-Douglas cost share of each factor in an industry commonly affects the sunk entry cost as well.

After paying the sunk entry cost (and realizing a productivity level), a firm must earn at least zero profit to remain and produce in the market. In other words, if the firm observes that its productivity is too low to earn a positive profit, it will shut down and exit. The minimum productivity requirement, or the productivity cutoff, for domestic production ϕ_i^* is thus determined by the following zero-profit condition:

$$r_i^H(\phi_i^{*H}) = \sigma f_i (s^H)^{\beta_i} (w^H)^{1-\beta_i} \quad (9)$$

In Industry i , all the firms whose productivity is higher than or equal to ϕ_i^{*H} will continue

operation, while less productive firms will exit.

The value of each firm is determined as the present discount value of the future profit flows, which is expressed as follows:

$$v_{i,\omega}^H(\phi_{i,\omega}) = \max \left\{ 0, \sum_{t=0}^{\infty} (1-\delta)^t \pi_{i,\omega}^H(\phi_{i,\omega}) \right\} = \max \left\{ 0, \frac{\pi_{i,\omega}^H(\phi_{i,\omega})}{\delta} \right\} \quad (10)$$

where $\delta < 1$ is an exogenous probability of firm death in each period. In the long run equilibrium, the expected value of entry, $V_{i,\omega}$, will equal the sunk entry cost for each firm in each industry. Since the expected value of entry is the expected value of the firm (or future profit stream) conditional on the *ex ante* probability of successful entry, the free-entry condition is as follows:

$$V_{i,\omega}^H = [1 - G(\phi_i^{*H})] \frac{\bar{\pi}_i^H}{\delta} = f_{ei}(s^H)^{\beta_i} (w^H)^{1-\beta_i} \quad (11)$$

where $\bar{\pi}_i^H$ represents the per-period expected future profit for the firm successfully entering into the market in Industry i . That is, $\bar{\pi}_i^H \equiv \pi_i^H(\bar{\phi}_i^\lambda)$ where $\bar{\phi}_i^\lambda$ is the average productivity of the successful entrees in the industry.⁹

In the case of an autarkic economy, by combining the zero profit condition (9) and the free entry condition (11), the following equation to determine the cutoff-level productivity

ϕ_i^{*H} is derived:

⁹ The average productivity of the successfully entering firms is determined by the *ex post* distribution of the productivities defined with the zero-profit cutoff productivity level: i.e.;

$$\bar{\phi}_i^\lambda = \bar{\phi}(\phi_i^{*\lambda}) = \left[\frac{1}{1 - G(\phi_i^{*\lambda})} \int_{\phi_i^{*\lambda}}^{\infty} \phi^{\sigma-1} g(\phi) d\phi \right]^{\frac{1}{\sigma-1}}$$

where $g(.) = G'(.)$ is a density function of productivity ϕ .

$$\frac{f_i}{\delta} \int_{\phi_i^{*H}}^{\infty} \left[\left(\frac{\phi}{\phi_i^{*H}} \right)^{\sigma-1} - 1 \right] g(\phi) d\phi = f_{ei} \quad (12)$$

where $g(\cdot) = G'(\cdot)$ is the common density function of productivity ϕ .¹⁰ The left-hand side of Equation (12) monotonically decreases as the value of ϕ_i^{*H} increases, and thus a unique value of ϕ_i^{*H} is identified since the right-hand side of the equation is constant.

Export

The main interest of this paper is a trading equilibrium, and I now analyze the decisions of the firms when a country is open to trade with the other country.

For each firm to export, it must incur per-year fixed costs for export, which depend on the domestic factor prices and industry factor intensity, as the fixed costs for domestic production and the sunk entry cost do. Specifically, the per-year fixed costs for export are described as $f_{xi}(s^H)^{\beta_i}(w^H)^{1-\beta_i}$, $f_{xi} > 0$. In addition, international trade is subject to variable “iceberg” shipping costs such that only a proportion $1/\tau_i$ ($\tau_i > 1$) of the shipped quantity of products reaches the other country. The variable costs are assumed to be symmetric between the two countries.

The optimal export price of the product of Firm ω in Home in Industry i ($p_{xi,\omega}^H$) is equal to the constant markup ($1/\rho$) over the marginal production cost inclusive of the iceberg transportation costs. That is;

$$p_{xi,\omega}^H(\phi) \equiv \tau_i \cdot p_{i,\omega}^H(\phi) = \frac{\tau_i (s^H)^{\beta_i} (w^H)^{1-\beta_i}}{\rho \phi_{i,\omega}} \quad (13)$$

¹⁰ See Appendix A for the derivation of Equation (12).

Accordingly, Firm ω 's revenue from export to the Foreign market is:

$$r_{xi,\omega}^H(\phi) = \alpha_i Y^F \left(\frac{\tau_i (s^H)^{\beta_i} (w^H)^{1-\beta_i}}{\rho \phi_{i,\omega} P_i^F} \right)^{1-\sigma}.$$

Firms produce either to serve only the domestic market or to serve both domestic and foreign markets, depending on their productivity.¹¹ Therefore, the total revenue of each firm is now as follows:

$$r_{i,\omega,total}^H(\phi) = r_{i,\omega}^H(\phi) \quad \text{if the firm serves only the domestic market;}$$

$$r_{i,\omega,total}^H(\phi) = r_{i,\omega}^H(\phi) + r_{xi,\omega}^H(\phi) \quad \text{if the firm also exports.}$$

As in the closed economy case, the zero-profit condition and the free-entry condition jointly identify the productivity cutoff at which additional profits from exporting are zero. The profit of each firm now consists of two parts:

$$\pi_{i,\omega,total}^H(\phi) = \pi_{i,\omega}^H(\phi) + \max\{0, \pi_{xi,\omega}^H(\phi)\} \quad (14)$$

$$\text{where } \pi_{i,\omega}^H(\phi) = \frac{r_{i,\omega}^H(\phi)}{\sigma} - f_i (s^H)^{\beta_i} (w^H)^{1-\beta_i};$$

$$\pi_{xi,\omega}^H(\phi) = \frac{r_{xi,\omega}^H(\phi)}{\sigma} - f_{xi} (s^H)^{\beta_i} (w^H)^{1-\beta_i}.$$

Accordingly, the zero-profit condition is two-fold, which consists of the following two equations:

Zero-profit condition for domestic production, which involves the domestic producer productivity cutoff ϕ_i^{*H} :

$$r_i^H(\phi_i^{*H}) = f_i (s^H)^{\beta_i} (w^H)^{1-\beta_i} \quad (15)$$

Zero-profit condition for export, which involves the exporter productivity cutoff ϕ_{xi}^{*H} :

¹¹ To preview the result, if they are sufficiently productive, domestic producers can also export.

$$r_{xi}^H(\phi_{xi}^{*H}) = \sigma f_{xi}(s^H)^{\beta_i} (w^H)^{1-\beta_i} \quad (16)$$

Equations (15) and (16) jointly determine the relationship between the two cutoffs ϕ_i^* and ϕ_{xi}^* for each country, as follows:

$$\phi_{xi}^{*H} = \Lambda_i^H \cdot \phi_i^{*H} \quad \text{for Home} \quad (17)$$

$$\phi_{xi}^{*F} = \Lambda_i^F \cdot \phi_i^{*F} \quad \text{for Foreign} \quad (18)$$

where $\Lambda_i^H = \tau_i \left(\frac{P_i^H}{P_i^F} \right) \left(\frac{Y^H}{Y^F} \cdot \frac{f_{xi}}{f_i} \right)^{\frac{1}{\sigma-1}}$ and $\Lambda_i^F = \tau_i \left(\frac{P_i^F}{P_i^H} \right) \left(\frac{Y^F}{Y^H} \cdot \frac{f_{xi}}{f_i} \right)^{\frac{1}{\sigma-1}}$,¹² and P_i^H and P_i^F are

the industry price indexes in Home and Foreign, respectively. Because empirical studies have shown that exporting firms tend to be more productive than non-exporters, I focus on the case where the productivity cutoff for export is higher than that for domestic production: i.e.,

$\phi_{xi}^{*H(F)} > \phi_i^{*H(F)}$, or $\Lambda_i^{H(F)} > 1$. This would be the case when the fixed costs for export is

sufficiently higher than fixed costs for (domestic) production ($f_{xi} > f_i$), and/or the variable

trade costs (τ_i) are sufficiently large. In this case, only a portion of firms that successfully

enter the domestic market can export, i.e., selection of exporters occurs.¹³ Of all the firms in

Home that draw a random productivity in return for the sunk entry cost, a fraction of $G(\phi_i^{*H})$

will exit because their revenues can not cover the fixed costs for domestic production. A

fraction $G(\phi_{xi}^{*H}) - G(\phi_i^{*H})$ of the firms will serve only the Home domestic market because

they will not be able to cover the higher fixed costs for export. Only the remaining firms (the

fraction of $1 - G(\phi_{xi}^{*H})$), which are the most productive, will be exporters.

¹² See Appendix A for the derivation of Equations (17) and (18).

¹³ $\Lambda_i^H > 1$ will also hold when the industry price index in Home is higher than that in Foreign ($P_i^H > P_i^F$), and/or the Home economy is larger than Foreign ($Y^H > Y^F$). However, this also implies that Λ_i^H could be less than one if Home price index is sufficiently lower than that of Foreign, and/or the Home economy is sufficiently smaller than the Foreign economy.

The free-entry condition also comprises two parts: the expected future profit stream from the domestic market, and the expected future profit from the export market multiplied by the probability of being an exporter conditional on the firm successfully entering and staying the domestic market. The value (or the expected total future profit) of Firm ω is:

$$v_{i,\omega}^H(\phi_{i,\omega}) = \max\left\{0, \frac{\pi_{i,\omega}^H(\phi_{i,\omega})}{\delta}\right\} + \chi_i^H \cdot \max\left\{0, \frac{\pi_{xi,\omega}^H(\phi_{i,\omega})}{\delta}\right\} \quad (19)$$

where $\chi_i^H \equiv \frac{1 - G(\phi_{xi}^{*H})}{1 - G(\phi_i^{*H})}$ is the probability of exporting conditional on the firm successfully

entering and producing in the domestic market. Hence, the free-entry condition with costly international trade is that the *ex ante* expected value of initial entry equals the sunk entry cost:

$$V_i^H = \frac{1 - G(\phi_i^{*H})}{\delta} [\bar{\pi}_i^H + \chi_i^H \bar{\pi}_{xi}^H] = f_{ei}(s^H)^{\beta_i} (w^H)^{1-\beta_i} \quad (20)$$

where $\bar{\pi}_i^H \equiv \pi_i^H(\bar{\phi}_i^H)$ is the per-period profit of the average domestic producer from the domestic sales, and $\bar{\pi}_{ix}^H \equiv \pi_{xi}^H(\bar{\phi}_{xi}^H)$ is the per-period profit of the average exporter from export sales.¹⁴

Combining this free-entry condition (20) with the zero-profit condition (15) and (16) yields the following equation¹⁵:

¹⁴ The average productivity level of the group of domestically-producing firms is defined with the cutoff productivity for domestic production in each country, as follows:

$$\bar{\phi}_i^{\lambda}(\phi_i^{*\lambda}) = \left[\frac{1}{1 - G(\phi_i^{*\lambda})} \int_{\phi_i^{*\lambda}}^{\infty} \phi^{\sigma-1} g(\phi) d\phi \right]^{\frac{1}{\sigma-1}}$$

Similarly, the average productivity level of the group of exporters is defined with the cutoff productivity for export:

$$\bar{\phi}_{xi}^{\lambda}(\phi_{xi}^{*\lambda}) = \left[\frac{1}{1 - G(\phi_{xi}^{*\lambda})} \int_{\phi_{xi}^{*\lambda}}^{\infty} \phi^{\sigma-1} g(\phi) d\phi \right]^{\frac{1}{\sigma-1}}$$

¹⁵ The derivation of Equation (21) is shown in the Appendix A.

$$\frac{f_i}{\delta} \int_{\phi_i^{*H}}^{\infty} \left[\left(\frac{\phi}{\phi_i^{*H}} \right)^{\sigma-1} - 1 \right] g(\phi) d\phi + \frac{f_{xi}}{\delta} \int_{\phi_{xi}^{*H}}^{\infty} \left[\left(\frac{\phi}{\phi_{xi}^{*H}} \right)^{\sigma-1} - 1 \right] g(\phi) d\phi = f_{ei} \quad (21)$$

The first term of the left-hand side of this equation is monotonically decreasing in ϕ_i^{*H} , and the second term is monotonically decreasing in ϕ_{xi}^{*H} . Since ϕ_{xi}^{*H} increases as ϕ_i^{*H} increases (from Equations (17) and (18), $\phi_{xi}^{*H(F)} = \Lambda_i^{H(F)} \cdot \phi_i^{*H(F)}$, $\Lambda_i^{H(F)} > 1$), the whole of the left-hand side of the equation monotonically decreases as the value of ϕ_i^{*H} increases. With the right-hand side being constant, this Equation (21) solves for the unique value of the domestic production cutoff ϕ_i^{*H} and accordingly the export cutoff ϕ_{xi}^{*H} .

Factor Prices

Because of fixed and variable trade costs, factor price equalization (FPE) fails. However, the relative prices of two factors will converge partially such that equilibrium relative factor prices will fall between their autarky and free trade levels. In autarky, the wage for skilled labor relative to that for the unskilled is lower in the skill-abundant Home. Opening the country to costly trade will result in an increase in the relative reward for the abundant factor in each country (i.e., s/w will rise in the Home and w/s will rise (or s/w will fall) in the Foreign), which will decrease the difference in relative factor prices between the two countries. That is;

$$\begin{pmatrix} \frac{s^H}{w^H} \\ \frac{s^F}{w^F} \end{pmatrix}^A < \begin{pmatrix} \frac{s^H}{w^H} \\ \frac{s^F}{w^F} \end{pmatrix}^{CT} < \begin{pmatrix} \frac{s^H}{w^H} \\ \frac{s^F}{w^F} \end{pmatrix}^{FT}$$

where A , CT , and FT indicate autarky, costly trade, and free trade, respectively.¹⁶ The right-hand side (the third term) of the inequality above will be equal to one when free trade leads to factor price equalization (FPE).¹⁷

This difference in equilibrium relative factor reward implies that the impacts of costly trade will differ across countries and industries due to factor proportion-based comparative advantage. The profits derived from exporting will also vary across countries, across industries, and across heterogeneous firms.

Probability of Exporting

Having analyzed both firm-level production heterogeneity and country-level factor prices in equilibrium, I unite them to analyze the determinants of a firm's exporting status. The *ex ante* probability for a domestic producer to be an exporter is determined by the two productivity cutoffs: ϕ_i^* for domestic production and ϕ_{xi}^* for export. That is, as previously defined, the probability is expressed as follows:

$$\chi_i^H \equiv \frac{1 - G(\phi_{xi}^{*H})}{1 - G(\phi_i^{*H})} < 1. \quad ^{18}$$

In the equilibrium, this probability equals the *ex post* fraction of exporting firms in all the domestically-producing firms. That is, denoting the mass of the continuum of actively-producing firms by M_i and that of exporting firms by M_{xi} ,

$$M_{xi}^H / M_i^H = \chi_i^H \quad (22)$$

The concern of this paper is documenting the determinants of the cross-industry patterns of

¹⁶ See Appendix A for demonstration for the equilibrium factor prices.

¹⁷ It can be shown that a free-trade equilibrium with FPE exists in this model economy. The author can provide the proof upon request.

¹⁸ The inequality follows $\phi_{xi}^{*H} > \phi_i^{*H}$ as Equation (17) (Equation (18) for Foreign) shows.

this probability of a domestic producer being an exporter. Before deriving a prediction, I introduce the following assumption on the distribution for firm productivity:

$$\text{Assumption: } G(\phi_i) = 1 - \left(\frac{\phi_i}{\underline{\phi}_i} \right)^k \text{ for } i = 1, 2, \dots, N; k > 2\sigma$$

That is, I assume that the *ex ante* distribution of firm productivity is a Pareto distribution.¹⁹ $\underline{\phi}_i$ is the minimum value for productivity drawn in Industry i ($\phi_i \in [\underline{\phi}_i, +\infty)$), and k is a shape parameter that indicates the dispersion of productivity distribution, which is assumed to be common across industries. I assume $k > 2\sigma$ for the variances of both drawn productivities and sizes of firms (measured as domestic sales) to be finite.²⁰

Now the following proposition is derived:

Proposition: Suppose $f_i = f$, $f_{xi} = f_x$, and $\tau_i = \tau$ for any $i = 1, 2, \dots, N$. Then, if

$$\frac{\bar{S}^H}{\bar{U}^H} > \frac{\bar{S}^F}{\bar{U}^F} \text{ and } \beta_1 < \beta_2 < \dots < \beta_N, \chi_1^H < \chi_2^H < \dots < \chi_N^H \text{ and}$$

$$\chi_1^F > \chi_2^F > \dots > \chi_N^F.$$

Proof: See Appendix A.

This proposition implies that if fixed costs for production and export differ across industries only due to the cross-industry variation of the cost shares of two factors,²¹ and the “iceberg” shipping costs are also the same for all industries, then the *ex ante* probability for a domestic

¹⁹ See Chaney (2008) for references evidencing that a Pareto distribution well approximates the observed distribution of the sizes of the U.S. firms. A Pareto distribution is also used frequently for the distribution of firm productivity in this type of models: for example, Helpman, Melitz and Yeaple (2004), Ghironi and Melitz (2005), Melitz and Ottaviano (2008), and Bernard, Redding and Schott (2007).

²⁰ For the variance of drawn productivity to be finite, it must be that $k > 2$. For the variance of the domestic sales of firms to be finite, $k > 2(\sigma-1)$. For these two conditions for k to be satisfied for any $\sigma > 1$, I assume $k > 2\sigma$.

²¹ Recall that both production fixed costs and export fixed costs depend on factor prices: $f_i(s^H)^{\beta_i}(w^H)^{1-\beta_i}$

and $f_{xi}(s^H)^{\beta_i}(w^H)^{1-\beta_i}$. The cost shares of the two factors in these fixed costs differ across industries.

Therefore, even though the parameters f and f_x are the same for all industries, the fixed costs still vary across industries.

producer to be an exporter, which is equal to the *ex post* fraction of exporting firms to all domestic firms, will be higher in an industry that uses more intensively a production factor with which a country is relatively well-endowed. That is, if other things are equal, for the (un)skilled labor-abundant Home (Foreign) country, a larger fraction of firms that are serving the domestic market will export as an industry is more (un)skilled-labor intensive.

The key determinant of the *ex ante* probability of a domestic producer being an exporter is the “gap” between the two productivity cutoffs—the minimum productivity level for domestic production and the minimum for export. The gap between the two cutoffs, which is measured as the ratio of the export productivity cutoff to the domestic production productivity cutoff (ϕ_{xi}^* / ϕ_i^*), thus decide the *ex post* fraction of exporters among active domestic firms. The predicted ranking of the exporter fractions that the proposition states is generated from the (reversed) ranking of the “gap” between the two productivity cutoffs in equilibrium. In other words, the “gap” is smaller in an industry with a stronger degree of comparative advantage (i.e., an industry that more intensively uses a factor with which the country is relatively well-endowed), as depicted in Figure 1. While the “gap” is defined as the ratio of the two productivity cutoffs, Figure 1 expresses the “gap” as a distance between the two cutoffs on a line (one can understand that the productivity levels in the figure are shown in a log scale).²² The mechanism that generates this cross-industry ranking of the productivity “gaps” is intuitively explained by competition in domestic factor markets. Consider the case for the skilled-labor abundant Home. When the country opens up to costly international trade, the potential profit will rise for firms with high productivity, as well as for new entrants that can possibly draw a high level of productivity, due to the additional sales opportunity in the

²² Figure 1 also normalizes the autarky productivity cutoffs for domestic production in all industries for an illustrative purpose.

foreign market. This will raise the domestic labor demand and thus increase domestic wages. The domestic wage increase results in the increase in production costs, and due to this production cost increase, all domestic firms will require a higher level of productivity for survival, thus raising the productivity cutoff for domestic production. This increase in the domestic-production productivity cutoff will occur in all industries, while the productivity increase will be more pronounced in more skill-intensive industries. The reason for this is that the increase in potential profit from export is larger in more skill-intensive (i.e., comparative-advantage) industries, and the increase in firms' factor demands will thus be larger in more skill-intensive industries. This results in a larger increase in the demand for skilled labor than in the unskilled-labor demand, and thus the relative price of skilled labor to the unskilled will rise. As a result, the increase in production costs will be larger and accordingly the rise in the minimum productivity level required for domestic production will be greater if the industry is more skill intensive. At the same time, for the "survivor" firms, exporting will be easier in more skill-intensive industries because of the country's comparative advantage. In costly-trade equilibrium, the relative price of skilled labor will be lower in the Home than the Foreign, and this relative factor-price advantage will be more pronounced if the industry is more skill intensive. This results in a lower minimum productivity level for exporting in that industry.

3. Data

The model predicts, as the Proposition in the last section states, that a larger fraction of firms that are active (i.e., producing and selling their products) in the domestic market will become exporters in an industry in which the country's comparative advantage is stronger.

This implies that, for each country, the ratio of exporters to all active firms in an industry can be ranked according to the industry's intensity of the use of the factor that is better-endowed in the country relative to the rest of the world. To test this prediction empirically, I need information on how many firms in each industry are active and how many out of those active firms export to other countries. I also need information on the factor intensity of each industry, as well as the factor abundance of countries in which the firms locate. In the current study, I use four countries for which at least limited data are available: Chile, Colombia, India, and the United States.

Chilean Data

For Chile, I employ a firm-level dataset from an annual manufacturing census conducted by the national statistical institute of the country (Instituto Nacional de Estadísticas: INE), which was compiled and documented in English through a World Bank project.²³ The manufacturing census dataset covers all establishments with ten or more employees. The dataset contains various kinds of information on each establishment including employment by type and the values of sales and exports. The dataset also contains the code of the industry that each firm belongs to, which is according to Chile's national classification of economic activities (Clasificador de Actividades Económicas, CIIU²⁴) at the four-digit level. Although the dataset covers the years 1979 through 1996, it has the export value of each firm only for 1990 through 1996. The dataset thus enables the calculation of the ratio of exporters to active firms and the skilled-labor intensity for various manufacturing industries for 1990 through 1996.

²³ See Roberts and Tybout (1996) for the summary of the project funded by the World Bank.

²⁴ CIIU is indeed equivalent to the International Standard Industry Classification (ISIC), Revision 2.

Colombian Data

The dataset for Colombia that I use in this study is from an annual census of manufacturing by Colombia's national statistical office (Departamento Administrativo Nacional de Estadística: DANE), which was also compiled as a part of the World Bank project. The Colombian manufacturing census contains a variety of information on manufacturing plants with ten or more employees. The dataset covers the years 1981 through 1991. The industry code is also available according to the International Standard Industry Classification (ISIC, Revision 2) at the four-digit level. The dataset allows for the calculation of the fraction of exporters among active firms and the skilled-labor intensity for each manufacturing industry for 1981 through 1991.

Indian Data

Information on India is originally sourced from the Annual Survey of Industries (ASI) conducted by the Ministry of Statistics and Programme Implementation of India. The survey covers all industrial units that are registered under the Factories Act with more than 20 employees. This paper uses data that are aggregated for each of the four-digit ISIC (Revision 2) industries from the original unit level data, which include the following industry-level variables: the numbers of industrial units, exporting units, skilled workers, and unskilled workers. The data are for a single year of the Indian fiscal year 1997/98 (the period from April 1, 1997 through March 31, 1998).²⁵

²⁵ I thank Jagadeesh Sivadasan for providing the aggregated data for India. Also see Sivadasan (2007) for the description of the original ASI data.

U.S. Data

For the United States, although I do not have equally detailed firm-level data as those for the previously-mentioned three countries, I have collected the necessary data from published sources. The U.S. Bureau of the Census (1992) provides the numbers of establishments and exporting establishments in each of twenty manufacturing industries classified according to the 1987 U.S. Standard Industry Classification (SIC) at the two-digit level, for the year 1992. Data on the number of production workers and the total employment in each two-digit U.S. SIC industry are available from the publications on the 1992 U.S. Census of Manufactures. These are used to measure the skilled-labor intensity of each manufacturing industry.

Factor Endowment Data

For the information on how well these four countries are endowed with (un)skilled labor (i.e., the skilled-to-unskilled labor ratio: S/U), I employ the ratio of human capital to labor ratio provided by Hall and Jones (1999) as my benchmark measure. They measure human capital per worker in a country using the average years of schooling in the population of the country and return-to-schooling estimates.^{26, 27} I also use data on educational attainment reported by Barro and Lee (2000) as an alternative measure of the countries' relative skill

²⁶ More specifically, they measure human capital per worker in a country (c) as $H_c / L_c = e^{\phi(E_c)}$, where E_c is the average years of schooling in the country's population measured by Barro and Lee (1993), and $\phi'(E)$ is an estimated return to schooling in a Mincerian wage regression that is reported by Psacharopoulos (1994). They apply a piecewise linear specification to $\phi(E)$ assuming that the return to schooling differs for each segment of year length of schooling. See Hall and Jones (1999) for more details.

²⁷ I also use another measure of human capital per worker relative to the United States reported by Klenow and Rodriguez-Clare (1997). Their way of estimating the human capital to labor ratios for countries is similar but slightly different from the method applied by Hall and Jones (1999). See Klenow and Rodriguez-Clare (1997) for the details. My empirical results, however, do not change between these two measures, and thus I report only the results with Hall & Jones' measure in the following part of this paper.

abundance for robustness checks. The details of this alternative measure are described in a later section.

Table 2a shows the relative skilled-labor abundance of the four countries according to the Hall and Jones' measure of human capital per worker. The summary statistics of the variable for 127 countries covered in their data are also presented for reference. All the numbers are based on the statistics weighted by the amount of labor reported in the source data. Similarly, Table 2b reports the relative skill abundance of the four countries according to Barro and Lee's measure of tertiary education completion in the total population over age 15, with the population-weighted summary statistics for 103 countries covered in their data. Both tables show that these four countries represent diverse groups of countries in terms of skill-labor abundance. That is, the United States is very skill rich, Chile is moderately skill abundant, Colombia is about the "middle,"²⁸ and India is skill scarce or unskilled-labor abundant.

4. Empirical Analysis

4.1. Individual Country Analysis

The theoretical two-country two-factor model suggests that if a country is more (un)skilled-labor abundant relative to the rest of the world, the fraction of exporting firms among all active firms in that country will be higher in more (un)skilled-labor intensive industries. To test this prediction, I apply the following empirical model for each individual country:

$$ex_share_i = \gamma + \theta \cdot skill_i + \varepsilon_i \quad (23)$$

²⁸ According to Hall and Jones' data, Colombia is a slightly less skill abundant country compared to the median and the mean of the 127 countries, while the country falls between the median and mean of the 103 countries in Barro and Lee's data.

where $ex_share_i = (\text{number of exporters}) / (\text{number of active firms})$ in Industry i , and $skill_i$ is the skilled-labor intensity of the industry.²⁹ The theoretical prediction is that the coefficient for the skilled-labor intensity (θ) will be larger (i.e., more positive or less negative) for the country with higher skilled-labor abundance. In the rest of this subsection, I test this prediction by estimating the regression equation (23) using the data for each of the four sample countries: Chile, Colombia, India, and the United States, and compare the coefficient θ estimated for each country.

Chile

For Chile, using the dataset described in the previous section, I compute each variable in Equation (23) for 25 manufacturing industries classified according to the three-digit ISIC.³⁰ Exporters are defined as firms with positive values of exports, and active firms are firms with positive total sales of goods. The skilled-labor intensity of each industry $skill_i$ is the share of skilled workers^{31, 32} in all workers employed in each industry.³³ For Chile, as well as for

²⁹ The measure of skilled-labor intensity is described for each country later in this subsection. Because the categories of workers in the data are different for each country, the definition of the industry skill intensity is not exactly the same for all four countries.

³⁰ The three-digit ISIC lists 28 manufacturing industries. I exclude the following four industries from the estimation: 314 (tobacco products), 353 (petroleum refineries), 354 (miscellaneous petroleum and coal products), and 390 (other manufacturing products). The last category is excluded because of its miscellaneous status. The first three categories are excluded because these industries are extremely concentrated (Carree *et al.*, 2000). In the data used in the present study, the number of active (domestic) firms is significantly lower in these industries compared to other three-digit industries in Chile, Colombia, and India. (Although industries are classified differently in the U.S. data, the number of firms in the U.S. data is also extremely small in industry categories corresponding to these three ISIC industries.) Alvarez and Lopez (2006) and Bergoeing and Repetto (2006), which use Chilean firm-level data, also exclude the tobacco and petroleum industries from their analyses because these industries “are organized as monopolies, operating with very few plants” (Bergoeing & Repetto, 2006).

³¹ The categories of workers in the dataset are more detailed. I define skilled workers as the total of owners, executives, white-collar administrative workers, and white-collar production workers. Unskilled workers are the rest of the workers employed; i.e., blue-collar production and non-production workers, workers at home, and salespersons in commission. Therefore, the unskilled-labor intensity of each industry equals $1 - skill_i$.

³² The proposition presented in the second section of this paper is based on the Cobb-Douglas cost share of skilled workers in an industry (β_i). However, as explained in Footnote 10, with an equilibrium relative wage (s/w) in a country, the ranking of industry skill intensity measured by the physical unit of labor ($S_i/(S_i+U_i)$) corresponds to the ranking of β_i .

Colombia in the following subsection, data are averaged over periods for cross-industry estimation; this is done to achieve a fair comparison of estimation results with those for India and the United States for which data are available only for a single year. Hence, for Chile, the average values of the variables over the years 1990 through 1996 are used for the analysis.³⁴

The result of the estimation by OLS is presented in Table 3, and the plot of the fractions of exporters against the industry skill intensities is shown with the fitted line in Figure 2. In Chile the correlation between the exporter fractions and the industry skill intensities is positive ($\hat{\theta} = 0.634$) and significant.

Colombia

Variables for estimating Equation (23) are computed from the previously-mentioned Colombian dataset for the 25 industries classified according to the three-digit ISIC. The value of each variable is the average from 1981 to 1991.³⁵ The definitions of an exporter and an active firm are the same as those in the Chilean case. The industry skilled-labor intensity is the share of workers in the categories of owners, management, skilled workers, and local and foreign technicians in all workers employed in each industry.³⁶

Table 4 shows the estimation result, and Figure 3 plots the fractions of exporters against the skilled-labor intensities of the 25 three-digit industries. The correlation between the exporter fractions and the industry skill intensities is not significant in Colombia

³³ The total employment in each industry, as well as the number of (un)skilled workers, is computed by aggregating for each industry the numbers of workers (in each category) hired by the firms in the dataset.

³⁴ I also estimated the coefficient theta using whole panel data for Chile (with time dummies, standard errors clustered by industry), and obtained virtually the same result for each country.

³⁵ The averaged data are used for the same reason as described for Chile in the previous subsection. Estimation with whole panel data does not alter the result, however.

³⁶ Unskilled labor is thus the sum of workers in other categories in the data (i.e., unskilled workers and apprentices).

($\hat{\theta} = -0.091$).

India

For India, I compute the variables for a regression from the data described in Section 3 for the 25 manufacturing industries classified according to the three-digit ISIC. Exporter fraction in each industry is measured as the number of exporting industrial units divided by the number of all units in the industry. The skilled-labor intensity of each industry is the share of non-production workers in all employees in the industry. The variables are for the single fiscal year 1997/98.

Table 5 presents the result of the estimation. In India, the correlation between the exporter fractions and the industry skill intensities is negative ($\hat{\theta} = -0.865$) and fairly significant. Figure 4 plots the exporter fractions vs the skilled-labor intensities of the 25 manufacturing industries and shows the fitted line together.

Table 6 summarizes the results of these individual country regressions for the three countries in order to compare the estimates of the coefficient for the industry skill intensity. For all three countries, the data are for the common 25 manufacturing industries classified according to the three-digit ISIC. The correlation estimated by each individual country regression is larger, or more positive, for a country with higher skill abundance, as the theoretical model suggests. The coefficient estimate is negative for India while it is positive for Chile, and the estimate for Colombia falls in between.

United States

Unlike for the other three countries, for the United States, industries are not classified according to the ISIC in the available data, but are classified according to the 1987 U.S. SIC at the two-digit level. I thus estimate Equation (23) for the United States with 17 manufacturing industries.³⁷ The exporter fraction (ex_share_i) is the number of exporting establishments divided by the number of (all) establishments in each industry. The industry skilled-labor intensity is measured as the share of non-production workers in all workers employed in each industry.³⁸ The variables are for the single year 1992.

The result of the estimation with the 17 manufacturing industries by OLS is presented in Table 7. Figure 5 displays the plot of the fractions of exporters against the industry skill intensities along with the fitted line. The correlation between the exporter fractions and the industry skill intensities is positive ($\hat{\theta} = 0.587$) and fairly significant in the United States.

Comparing Four Countries

The coefficient estimates for the industry skill intensity (θ) for the United States is not directly comparable with the estimates for the other three countries due to the difference in industry classification. For the cross-country comparison of the coefficient, I compute for Chile, Colombia, and India the exporter fractions and skill intensities in the two-digit U.S. SIC industries, using the concordance between the three-digit ISIC and the two-digit U.S. SIC, which is presented in Table 9. The re-classified data are used to re-estimate Equation (23) for

³⁷ There are 20 two-digit U.S. SIC manufacturing industries, but as for the other three countries, for the United States I exclude tobacco, petroleum and coal, and miscellaneous industries from estimation. The following three categories in the two-digit U.S. SIC corresponds to these three industries and thus are excluded: 21 (tobacco products), 29 (petroleum and coal products), and 39 (misc. manufacturing industries).

³⁸ More specifically, since in the Census of Manufactures the number of production workers is available for each manufacturing industry, I first calculate *unskilled-labor* intensity that is defined as the share of production workers in the total employment, and then compute *skilled-labor* intensity as one minus *unskilled-labor* intensity.

each of these three countries with the 17 two-digit U.S. SIC manufacturing industries. Table 8 compares the coefficients estimated for Chile, Colombia, India, and the United States.³⁹ The table shows that the relative sizes of the coefficients correspond to the relative skill abundance of these countries. That is, the correlation between the exporter fractions and industry skill intensities is the largest (most positive) for the most skill abundant United States, the second for Chile, the third for Colombia, and the smallest (most negative) for the least skill abundant India. This result is consistent with the case for the 25 three-digit ISIC industries shown in Table 6, and also with the theoretical prediction.

Impact of Sample Truncation

As described in the previous section, manufacturing census data for these countries exclude small firms whose employment is below the threshold level.⁴⁰ This omission of small firms might cause bias in estimation, in particular if the fraction of exporters among domestic firms in a sample systematically overestimate or underestimate the fraction in a population in relation to industry skill intensities. This possibility of estimation bias is examined in Appendix B; however, the exclusion of small firms should not affect the result of the present empirical analysis.

4.2. Pooled Analysis

The predicted relationship among the relative factor abundance of countries, relative

³⁹ For Chile and India, the coefficient estimates with the 17 two-digit U.S. SIC industries are not significant whereas the estimates with the 25 three-digit ISIC industries are significant at least at the 10% level. This can be explained by the aggregation of the industries. The aggregation of the 25 manufacturing industries to the 17 reduces the variance of the exporter fractions, which makes the size of the slope coefficient smaller. The aggregation also reduces the variance of the skill intensities among industries, which makes the standard error of the estimate larger.

⁴⁰ The U.S. Census of Manufactures also omits small firms that are excused from filing reports. See 1992 Census of Manufactures General Summary (MC92-S-1, pp. VII-IX) for the details of company coverage in the census.

factor intensities of industries, and the ratio of exporters to all active firms has been confirmed by individual country regressions in the previous section. This quasi-Heckscher-Ohlin prediction can be tested more formally using the following empirical model:

$$ex_share_{ic} = \gamma_c + \Pi_c \cdot skill_i + \varepsilon_{ic} \quad (24)$$

where i indexes an industry and c indexes a country. The coefficient Π_c for the industry skilled-labor intensity, as well as the constant term γ_c , being indexed by c means that these parameters differ across countries. In particular, the theoretical prediction is that the slope coefficient Π_c will be larger (more positive or less negative) for a country with a higher relative skilled-labor abundance, and smaller (less positive or more negative) for a country with a lower relative skilled-labor abundance (or a higher relative unskilled-labor abundance). To capture this correlation between the coefficient Π_c and the skill abundance of a country, the following structure is imposed:

$$\Pi_c = \Pi((S/U)_c) = \theta_1 + \theta_2 \cdot \log(S/U)_c \quad (25)$$

where $(S/U)_c$ is the skilled-labor to unskilled-labor ratio of Country c .⁴¹ By substituting (25) for (24), the following equation is derived:

$$ex_share_{ic} = \gamma_c + \theta_1 \cdot skill_i + \theta_2 \cdot skill_i \cdot \log(S/U)_c + \varepsilon_{ic} \quad (26)$$

This equation is estimated with pooled data for the four countries (Chile, Colombia, India, and the United States) and the 17 manufacturing industries classified according to the two-digit 1987 U.S. SIC. The pooled data allows for the inclusion of industry dummies in estimation to control for the effects of industry-specific factors other than the skill intensity, such as fixed and variable costs for export. (Recall that in Section 2 the theoretical model derives quasi-

⁴¹ The advantage of the log-scaled measure of relative factor abundance is that the size (absolute value) of the coefficient θ_2 will be invariant to which of S or U is the denominator of the measure.

Heckscher-Ohlin prediction when the (factor-price-adjusted) fixed costs for production, fixed costs for exporting, and variable shipping costs are the same across industries. These costs, however, are generally not the same.⁴²⁾ Hence, the equation is estimated in the following form:

$$ex_share_{ic} = \theta_2 \cdot skill_i \cdot \log(S/U)_c + \gamma_c + \eta_i + \varepsilon_{ic} \quad (26.2)$$

where γ_c and η_i are series of industry-specific and country-specific intercepts, respectively.⁴³

The fraction of exporters among active firms in each industry (ex_share_{ic}) is obtained from the data for each individual country. For Chile, the variable is of the average over the years 1990 through 1996; for Colombia, the variable is of the average over 1981 through 1991; for India, the variable is for the fiscal year 1997/98; and for the United States, the variable is for the year 1992. The skilled-labor to unskilled-labor ratio in each country ($(S/U)_c$) is measured as the human capital to labor ratio reported by Hall and Jones (1999). The variable $skill_i$ is now defined as the (Cobb-Douglas) cost share of skilled labor in each industry, which is assumed to be common across countries in the theoretical model. The cost-share measure, rather than the skill-intensity measure based on the physical amount of labor, is chosen because while the Cobb-Douglas cost share is the same for all countries, the employment-based intensity of each type of labor will differ across countries in general due to the difference in relative wage (s/w) in the costly-trade equilibrium.⁴⁴ This common cost-share variable is measured as wage payments to non-production workers as the share in the total

⁴² For this reason, it is ideal to control for these industry-specific costs in individual regressions in the previous subsection. However, industry-specific dummies cannot be used since the observations in individual country data are unique for each industry. In addition, no relevant measures of these costs are available. Nevertheless, the result of the individual country analysis is valid as far as these industry-specific costs are symmetric or invariant across countries.

⁴³ Note that the first term ($\theta_1 \cdot skill_i$) of Equation (26) is dropped from the estimation due to the inclusion of industry-specific dummies, because the industry skill intensity is unique for each industry.

⁴⁴ See Footnote 8.

annual payroll in each industry, using the data in the 1992 U.S. Census of Manufactures. The skilled-labor cost shares in the 17 two-digit U.S. SIC manufacturing industries are shown in Table 10.

The result of the estimation of Equation (26.2) is presented in Table 11. The positive and significant (at the 4% level) estimate $\hat{\theta}_2$ suggests that correlation between the exporter fractions and industry skill intensities (defined by the cost shares) is larger (or more positive) for a country with a higher relative skill abundance. This result of the pooled-data analysis confirms the result of the individual country analysis, and thus supports the theoretical prediction.⁴⁵

4.3. Robustness Check of Pooled Analysis

Although non-production workers or white-collar workers are frequently used in empirical studies to represent skilled labor, these are crude proxies. A more desirable measure is to categorize workers according to their (potential) skill levels such as educational attainment. To check the robustness of the result of the pooled regression in the previous subsection, I employ a measure of industry skill intensity proposed by Morrow (2008). He uses data from the March U.S. Current Population Survey for the years 1988-92 that contain information on incomes and educational attainment of workers employed in various industries. He computes the Cobb-Douglas cost share of skilled workers using the share of employees in each educational category and the wage levels of workers in an educational category relative to the wage level of workers in other categories estimated from a Mincerian wage regression. While he reports the information for the three-digit ISIC manufacturing industries, for the

⁴⁵ See Appendix C for further empirical exercise.

current study, I use this information to compute the skilled-labor cost shares for the two-digit U.S. SIC industries. I define skilled labor as workers with one or more years of college education. The details of the computation are described in Appendix D. The obtained skilled-labor cost shares in the 17 two-digit U.S. SIC manufacturing industries are listed in Table 12.

Because the industry skill intensity is now measured based on the educational attainment of workers, for consistency I also employ an educational attainment-based measure for the countries' relative abundance of skilled labor, $(S/U)_c$. Specifically, I use the percentage of the population that has attained tertiary education reported by Barro and Lee (2000). The percentages of tertiary education attainment for Chile, Colombia, India, and the United States are shown in Table 13.⁴⁶

Using these alternative measures of industry skill intensity and country skill abundance, Equation (26.2) is re-estimated with data for the four countries and 17 manufacturing industries. The result is presented in Table 14. A positive coefficient is estimated ($\hat{\theta}_2 = 0.277$) at the 5% level of significance (p-value = 0.018), which indicates that the estimated relationship among the factor abundance of countries, the skill intensities of industries, and the exporter fractions is robust across different measures of country factor abundance and industry skill intensity.⁴⁷

4.4. Factor Prices

In the current model, the mechanism that determines the cross-industry patterns of

⁴⁶ Since the exporter fractions are measured in different periods for each country, the educational attainment data for different periods are employed for each country to have the periods of the two variables being consistent. See Table 13 for the data periods for each country.

⁴⁷ The equation is also estimated using the alternative measure only for either industry skill intensity or for country skill abundance, maintaining the benchmark measure for the other variable. In any case, the estimated coefficient is positive and significant at the 5% level or more.

exporter fraction operates based on the relative prices of the two factors. As described in Section 2, in the costly-trade equilibrium, the relative wage is not equalized between countries. This relative wage difference creates the variation in the exporter fractions between comparative-advantage industries and comparative-disadvantage industries. To confirm this mechanism, in this subsection, I estimate the exporter fraction equation using wage data.

The source of information on wages is the Occupational Wages around the World (OWW) Database, an NBER dataset provided by Freeman and Oostendorp (2000). This is a comprehensive dataset of wages of various occupations in a large number of countries. The occupational wage data in the OWW Database are derived from the “October Inquiry,” which is a wage survey conducted by the International Labour Organization (ILO).⁴⁸ However, the ILO’s data, which are based on reports from national governments, involve problems such as inconsistency in wage format (e.g., weekly or monthly, minimum or average), missing data, and erroneous records. Therefore, in the OWW Database, the original October Inquiry data have been cleaned and standardized by calibration.⁴⁹ The OWW Database thus provides comparable wage data for a large number of occupations in many countries. In the current paper, I use an updated version of the OWW database by Oostendorp (2005) that covers 161 occupations (in various industries including services and the government sector) in 137 countries for the years 1983 through 2003.⁵⁰ The numbers of occupations and years covered in the database significantly vary across countries, however. For the four countries examined in the current study, wage data are available for the following years and numbers of occupations:

⁴⁸ The original ILO data are available at <http://laborsta.ilo.org/>. Also see Freeman and Oostendorp (2000) for the description of ILO’s October Inquiry.

⁴⁹ See Freeman and Oostendorp (2000) and Oostendorp (2005) for the details of the procedure of data calibration and standardization.

⁵⁰ The database is available at <http://www.nber.org/oww/>. Specifically, I employ the data on wages with country-specific and uniform calibration and lexicographic weighting (the variable “x3wl”) in the database.

for Chile, 89 to 134 occupations for 1984-86; for Colombia, 41 to 124 occupations for 1988-90; for India, 13 to 93 occupations for 1985-2000; and for the United States, 11 to 152 occupations for 1984-2002.

The skilled-labor wage relative to unskilled-labor wage, s/w , needs to be measured for each country. Since both numbers and types of occupations reported in the dataset vary across countries and years, I calculate the relative wage (s/w) in the following three ways: (i) taking the ratio of the highest occupational wage to the lowest (whatever these occupations are); (ii) dividing occupations into ten groups by wage deciles and taking the ratio of the mean wage in the highest-wage group to the mean wage in the lowest-wage group; and (iii) taking the ratio of the 90th percentile wage to the 10th percentile wage. After computing these three relative wage measures for each of the four countries for each year, I select the values of the three variables for the following period to match the wage data period to that of the exporter fraction for each country: for Chile, the averages over 1984-86;⁵¹ for Colombia, the averages over 1988-90;⁵² for India, the averages of 1997 and 1998; and for the United States, the year 1992. Table 15 lists the values of the relative skilled-to-unskilled wage in the three measures for each country.⁵³ The table shows that the relative wage reflects the relative skilled-labor abundance of the countries, except for Chile and Colombia. Between these two “medium” countries, the relative positions in terms of comparative advantage are reversed when they are measured by the relative wage.

The quasi-Heckscher-Ohlin prediction that the fraction of exporters among active

⁵¹ The periods do not match the ones for the exporter fractions (1990-96), but these are only periods for which the wage data are available for Chile.

⁵² The periods do not completely match the ones for the exporter fractions (1981-91), but these are only periods for which the wage data are available for Colombia.

⁵³ Note that these three relative wage measures are based on different sets of occupations for different countries. In the following subsection, I estimate the same equation using alternative relative wage measures that are based on the same set of occupations for all four countries.

domestic firms is higher in comparative-advantage industries for each country is tested using these three measures of the factor price ratio. The same empirical model as in the previous subsections is applied, but the skilled-to-unskilled labor ratio (S/U) is now replaced with the skilled-to-unskilled wage ratio (s/w), and thus the regression equation is as follows:

$$ex_share_{ic} = \psi \cdot skill_i \cdot \log(s/w)_c + \gamma_c + \eta_i + \varepsilon_{ic} \quad (27)$$

η_i and γ_c are industry- and country-specific intercepts, respectively, as in Equation (26.2). The same 17 two-digit U.S. SIC manufacturing industries are used for estimation. As in Subsection 4.(2), the industry skilled-labor cost share ($skill_i$) is measured as the wages to non-production workers as the share in the total payroll (in Table 10). Note that since the relative price of skilled labor (s/w) is lower in a more skill-abundant country, the model expects ψ to be *negative*.

The results of the estimation of Equation (27) using the three relative wage measures are presented in Table 16. With any wage measure, the estimate of ψ is negative and significant at the 5% level (p-value is between 0.019 and 0.040).⁵⁴ This indicates that the correlation between the exporter fraction and industry skill intensity (measured as the cost share) is larger in a country where the skilled labor is relatively cheaper, which is consistent with the prediction.

Relative Wage Measures Based on Same Occupations

Since the three measures of relative wage (s/w) are based on a different set of occupations for each country, the measured cross-country variation in the relative wage might be simply due to the difference of occupation composition. For instance, the large gap

⁵⁴ The equation is also estimated using the measure of skilled-labor cost share based on workers' educational attainment (following Morrow, 2008). The results do not change: with each relative wage measure, a similar size of the coefficient is estimated at least at the 5% level of significance.

between the measured wages of skilled and unskilled workers in India may not reflect the relative unskilled-labor abundance of the country, but instead may be due to the fact that data for India contain extremely well-paid occupations that are not covered in data for other countries. To address this potential measurement issue, in this subsection, I construct relative wage measures that are adjusted for occupation composition, and estimate Equation (27) with those alternative measures to check the robustness of the results presented above.

I first select a set of occupations that is in common across four countries. The occupation set consists of 25 occupations selected based on the availability of wage data in the OWW2 dataset. These 25 occupations are observed for Chile in 1985-86, for Colombia in 1988,⁵⁵ for India in 1997-98, and for the United States in 1992.⁵⁶ Based on this common occupation set, I compute the following three measures of skilled-to-unskilled wage ratio, which are similar to the relative wage measures used for the preceding estimation: (i) the ratio of the highest wage to the lowest wage in each country (maximum to minimum wage ratio); (ii) the ratio of the mean wage of the three highest-wage occupations to the mean wage of the three lowest-wage occupations (the top10% to the bottom10% mean wage ratio); and (iii) the ratio of the 90th percentile wage to the 10th percentile wage (the top 90th to the bottom 10th percentile wage ratio). The values of the three relative wage measures for each country are shown in Table 17.⁵⁷

These three alternative wage measures are used to re-estimate Equation (27) for the

⁵⁵ The availability of wage data in the dataset is the most limited for Colombia among the four countries. In addition, sets of data-available occupations for Colombia substantially differ across years. Therefore, to maximize the number of occupations in a common set to all four countries, I select a single year 1988 for Colombia. Chilean wage data in 1984 are also omitted for the same reason.

⁵⁶ These 25 industries are, in the occupation codes in the ILO October Inquiry: 30, 36, 59, 65, 67, 70, 82, 84, 85, 88, 90, 91, 95, 96, 97, 99, 100, 129, 130, 131, 133, 134, 135, 140, and 141. These occupations include a computer programmer, which is the best-paid occupation among these occupations in all four countries, and a laborer, which is one of the least-paid occupations in every country.

⁵⁷ Note that the order reversal between Chile and Colombia is also observed in these alternative wage measures.

four countries for the 17 two-digit U.S. SIC industries. The results are presented in Table 18, and are very similar to the results of the preceding estimation in Table 16. These results imply that (i) the relative wage measures used for the first estimation, although they are not adjusted for occupation composition, are well reflecting the countries' relative factor abundance, and (ii) the relative wage-driven mechanism of the theoretical model is empirically supported.

5. Conclusion

This paper investigates what patterns of the fractions of exporters among domestic firms emerge when countries and industries are asymmetric. The model of a two-country, two-factor and many-industry economy with productivity-heterogeneous firms, which is an extension of the two-factor, two-country and two-industry framework by Bernard, Redding and Schott (2007), suggests that a country's comparative advantage in terms of relative factor abundance explains the cross-industry and cross-country patterns of exporter selection. That is, the probability that a domestic producer will be an exporter is higher in the country's comparative-advantage industries. Furthermore, the fractions of exporters among domestic firms can be ranked according to the order of the industries' intensity of a production factor with which the country is relatively well-endowed. This quasi-Heckscher-Ohlin prediction about exporter fractions is empirically tested using data for manufacturing firms in Chile, Colombia, India, and the United States. The result of the analysis confirms the quasi-Heckscher-Ohlin pattern: the correlation between exporter fractions and the skill intensity of industries is larger, or more positive, for a country with higher skilled-labor abundance. This empirical finding is robust across alternative measures of both industry relative factor intensity and country relative factor abundance.

By empirically demonstrating the effect of factor proportion on the selection of exporters in different industries and countries, this paper highlights one role of comparative advantage that has not been adequately explored. The result of this study implies that, through the exporter selection, the influence of a country's comparative advantage can be more pronounced in the industrial composition of the country's export than in that of the country's domestic production, at least in terms of the extensive margin.

The empirical analysis in this paper is in fact based on data for a limited number of countries. Having more countries in a sample would be desirable to more strongly confirm the theoretical quasi-Heckscher-Ohlin prediction. Nevertheless, the four sample countries in this paper represent a variety of country groups in terms of relative skilled-labor abundance, and the empirical result clearly demonstrates a comparative advantage-driven variation in the patterns of exporter selection among countries.

References

- [1] Aitken, B., G. Hanson, and A. Harrison (1997), "Spillovers, Foreign Investment, and Export Behavior," *Journal of International Economics*, Vol. 43, No. 1-2, pp. 103-132
- [2] Alvarez, R. and R. A. Lopez (2005), "Exporting and Performance: Evidence from Chilean Plants," *Canadian Journal of Economics*, Vol. 38, No. 4, pp. 1384-1400
- [3] Alvarez, R. and R. A. Lopez (2006), "Entry and Exit in International Markets: Evidence from Chilean Data," CAEPR Working Paper No. 2006-014, Center for Applied Economics and Policy Research, Indiana University
- [4] Aw, B.Y., M. J. Roberts, and T. Winston (2007), "Export Market Participation, Investment in R&D and Worker Training, and the Evolution of Firm Productivity," *The World Economy*, Vol. 30, No. 1, pp. 83-104
- [5] Baldwin, R. E. (1971), "Determinants of the Commodity Structure of U.S. Trade," *American Economic Review*, Vol. 61, No. 1, pp. 126-146
- [6] Baldwin, J. R. and W. Gu (2003), "Export-market Participation and Productivity Performance in Canadian Manufacturing," *Canadian Journal of Economics*, Vol. 36, No. 3, pp. 634-657
- [7] Banerjee, A. V. and E. Duflo (2005), "Growth Theory through the Lens of Development Economics," Aghion, P. and S. N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 1, Part 1, pp. 473-552
- [8] Barro, R. J. and J. Lee (1993), "International Comparisons of Educational Attainment," *Journal of Monetary Economics*, Vol. 32, No. 3, pp. 363-394
- [9] Barro, R. J. and J. Lee (2000), "International Data on Educational Attainment: Updates and Implications," CID Working Paper No. 42, Harvard University
- [10] Bergoeing, R. and A. Repetto (2006), "Micro Efficiency and Aggregate Growth in Chile," *Cuadernos de Economia*, Vol. 43, No. 127, pp. 169-191
- [11] Bernard, A. B., J. Eaton, J. B. Jensen, and S. Kortum (2003), "Plants and Productivity in International Trade," *American Economic Review*, Vol. 93, No. 4, pp. 1268-1290
- [12] Bernard, A. B. and J. B. Jensen (1995), "Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987," *Brookings Papers on Economic Activity, Microeconomics*, Vol. 1995, pp. 67-119
- [13] Bernard, A. B., S. J. Redding, and P. K. Schott (2007), "Comparative Advantage and Heterogeneous Firms," *Review of Economic Studies*, Vol. 74, No. 1, pp. 31-66

- [14] Bils, M. and P. J. Klenow (2000), "Does Schooling Cause Growth?," *American Economic Review*, Vol. 90, No. 5, pp. 1160-1183
- [15] Blalock, G. and P. J. Gertler (2004), "Learning from Exporting Revisited in A Less Developed Setting," *Journal of Development Economics*, Vol. 75, No. 2, pp. 397-416
- [16] Castellani, D. and A. Zanfei (2007), "Internationalisation, Innovation and Productivity: How Do Firms Differ in Italy?," *The World Economy*, Vol. 30, No. 1, pp. 156-176
- [17] Carree, M. A., L. Klamp, and A. R. Thurik (2000), "Productivity Convergence in OECD Manufacturing Industries," *Economic Letters*, Vol. 66, No. 3, pp. 337-345
- [18] Chaney, T. (2008), "Distorted Gravity: The Intensive and Extensive Margins of International Trade," mimeo.
- [19] Clerides, S. K., S. Lach, and J. R. Tybout (1998), "Is Learning by Exporting Important? Micro-dynamic Evidence from Colombia, Mexico, and Morocco," *Quarterly Journal of Economics*, Vol. 113, No. 3, pp. 903-947
- [20] Deardorff, A. V. (1980), "The General Validity of Law of Comparative Advantage," *Journal of Political Economy*, Vol. 88, No. 5, pp. 941-957
- [21] Deardorff, A. V. (1982), "The General Validity of the Heckscher-Ohlin Theorem," *American Economic Review*, Vol. 72, No. 4, pp. 683-694
- [22] Deardorff, A. V. (1984), "Testing Trade Theories and Predicting Trade Flows," Jones, R. W. and P. B. Kenen, eds., *Handbook of International Economics*, Vol. 1, pp. 467-517
- [23] Dixit, A. K. and V. Norman (1980), *Theory of International Trade*, Cambridge University Press, Cambridge, U.K.
- [24] Dornbusch, R., S. Fischer, and P. A. Samuelson (1980), "Heckscher-Ohlin Trade Theory with a Continuum of Goods," *Quarterly Journal of Economics*, Vol. 95, No. 2, pp. 823-839
- [25] Ederington, J. and P. McCalman (2008), "Endogenous Firm Heterogeneity and the Dynamics of Trade Liberalization," *Journal of International Economics*, Vol. 74, No. 2, pp. 422-440
- [26] Falvey, R., D. Greenaway, and Z. Yu (2004), "Intra-industry Trade Between Asymmetric Countries with Heterogeneous Firms," GEP Research Paper 2004/05, Leverhulme Centre for Research on Globalisation and Economic Policy, University of Nottingham
- [27] Feenstra, R. C. and H. L. Kee (2008), "Export Variety and Country Productivity: Estimating the Monopolistic Competition Model with Endogenous Productivity," *Journal of International Economics*, Vol. 74, No. 2, pp. 500-518

- [28] Freeman, R. B. and R. H. Oostendorp (2000), "Wages Across the World: Pay Across Occupations and Countries," NBER Working Paper No. 8058
- [29] Ghironi, F. and M. J. Melitz (2005), "International Trade and Macroeconomic Dynamics with Heterogeneous Firms," *Quarterly Journal of Economics*, Vol. 120, No. 3, pp. 865-915
- [30] Girma, S., R. Kneller, and M. Pisu (2005), "Exports versus FDI: An Empirical Test," *Weltwirtschaftliches Archiv*, Vol. 141, No. 2, pp. 193-218
- [31] Greenaway, D. and R. Kneller (2007), "Firm Heterogeneity, Exporting and Foreign Direct Investment," *Economic Journal*, Vol. 117, No. 517, pp. F134-F161
- [32] Greenaway, D. and Z. Yu (2004), "Firm Level Interactions Between Exporting and Productivity: Industry-specific Evidence," *Weltwirtschaftliches Archiv*, Vol. 140, No. 3, pp. 376-392
- [33] Hall, R. E. and C. I. Jones (1999), "Why Do Some Countries Produce So Much More Output Per Worker Than Others?," *Quarterly Journal of Economics*, Vol. 114, No. 1, pp. 83-116
- [34] Hallak, J. C. and J. Sivadasan (2006), "Productivity, Quality and Export Behavior under Minimum Quality Requirements," Mimeo, University of Michigan
- [35] Harkness, J. (1978), "Factor Abundance and Comparative Advantage," *American Economic Review*, Vol. 68, No. 5, pp. 784-800
- [36] Helpman, E. (1981), "International Trade in the Presence of Product Differentiation, Economies of Scale and Monopolistic Competition: A Chamberlin-Heckscher-Ohlin Approach," *Journal of International Economics*, Vol. 11, No. 3, pp. 305-340
- [37] Helpman, E. (2006), "Trade, FDI, and the Organization of Firms," *Journal of Economic Literature*, Vol. 33, No. 3, pp. 589-630
- [38] Helpman, E. and P. R. Krugman (1985), *Market Structure and Foreign Trade*, MIT Press, Cambridge, M.A.
- [39] Helpman, E., M. J. Melitz, and S. R. Yeaple (2004), "Export versus FDI with Heterogeneous Firms," *American Economic Review*, Vol. 94, No. 1, pp. 300-316
- [40] Hendricks, L. (2002), "How Important Is Human Capital for Development? Evidence from Immigrant Earnings," *American Economic Review*, Vol. 92, No. 1, pp. 198-219
- [41] Klenow, P. J. and A. Rodriguez-Clare (1997), "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?," *NBER Macroeconomics Annual*, Vol. 12, pp. 73-103

- [42] Krugman, P. R. (1979), "Increasing Returns, Monopolistic Competition, and International Trade," *Journal of International Economics*, Vol. 9, No. 4, pp. 469-479
- [43] Lopez, R. A. (2005), "Trade and Growth: Reconciling the Macroeconomic and Microeconomic Evidence," *Journal of Economic Surveys*, Vol. 19, No. 4, pp. 623-648
- [44] Melitz, M. J. (2003), "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, Vol. 71, No. 6, pp. 1695-1725
- [45] Melitz, M. J. and G. I. P. Ottaviano (2008), "Market Size, Trade, and Productivity," *Review of Economic Studies*, Vol. 75, No. 1, pp. 295-316
- [46] Melvin, J. R. (1968), "Production and Trade with Two Factors and Three Goods," *American Economic Review*, Vol. 58, No. 5, pp. 1249-1268
- [47] Morrow, P. M. (2008), "East is East and West is West: A Ricardian-Heckscher-Ohlin Model of Comparative Advantage," Mimeo, University of Toronto
- [48] Oostendorp, R. H. (2005), "The Standardized ILO October Inquiry 1983-2003," Mimeo, Free University Amsterdam
- [49] Psacharopoulos, G. (1994), "Returns to Investment in Education: A Global Update," *World Development*, Vol. 22, No. 9, pp. 1325-1343
- [50] Psacharopoulos, G. and Y. C. Ng (1992), "Earnings and Education in Latin America: Assessing Priorities for Schooling Investments," World Bank Policy Research Working Paper No. 1056
- [51] Psacharopoulos, G. and H. A. Patrinos (2002), "Returns to Investment in Education: A Further Update," World Bank Policy Research Working Paper No. 2881
- [52] Roberts, M. J. and J. R. Tybout, eds. (1996), *Industrial Evolution in Developing Countries*, Oxford University Press, New York, N.Y.
- [53] Roberts, M. and J. Tybout (1997), "The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs," *American Economic Review*, Vol. 87, No. 4, pp. 545-564
- [54] Romalis, J. (2004), "Factor Proportions and the Structure of Commodity Trade," *American Economic Review*, Vol. 94, No. 1, pp. 67-97
- [55] Samuelson, P. A. (1949), "International Factor-Price Equalization Once Again," *Economic Journal*, Vol. 59, No. 234, pp. 181-197

- [56] Schott, P. K. (2003), "One Size Fits All? Heckscher-Olin Specialization in Global Production," *American Economic Review*, Vol. 93, No.3, pp. 686-708
- [57] Sivadasan, J. (2007), "Product Market Liberalization and Productivity: Evidence from India," Mimeo, University of Michigan
- [58] Stern, R. M. and K. E. Maskus (1981), "Determinants of the Structure of U.S. Foreign Trade, 1958-76," *Journal of International Economics*, Vol. 11, No. 2, pp. 207-224
- [59] Stolper, W. F. and P. A. Samuelson (1941), "Protection and Real Wage," *Review of Economic Studies*, Vol. 9, No. 1, pp. 58-73
- [60] U. S. Bureau of the Census (1992), *Selected Characteristics of Manufacturing and Wholesale Establishments That Export: 1992*, Manufacturing Analytical Report Series AR92-2, U. S. Department of Commerce, Washington D.C.
- [61] Wagner, J. (2007), "Exports and Productivity: A Survey of the Evidence from Firm-level Data," *The World Economy*, Vol. 30, No. 1, pp. 60-82
- [62] World Bank (2006), *World Development Indicators 2006*, Washington D.C.
- [63] Yeaple, S. R. (2005), "A Simple Model of Firm Heterogeneity, International Trade, and Wages," *Journal of International Economics*, Vol. 65, No. 1, pp. 1-20

Appendix A

1. Derivation of Equation (12):

Note, from Equation (6), that the ratio of the revenues of two firms with different productivities is expressed with the ratio of those firms' productivities, such as follows:

$$\frac{r_i(\phi')}{r_i(\phi)} = \left(\frac{\phi'}{\phi}\right)^{\sigma-1} \Leftrightarrow r_i(\phi') = \left(\frac{\phi'}{\phi}\right)^{\sigma-1} r_i(\phi) \quad (\text{A.1})$$

Using this relationship, as well as Equation (7) for an individual firm's profit and Equation (9) for the revenue of the firm with the cutoff-level productivity, the free-entry condition (11) becomes as follows:

$$\begin{aligned} [1 - G(\phi_i^{*\lambda})] \frac{\bar{\pi}_i^\lambda}{\delta} &= f_{ei}(s^\lambda)^{\beta_i} (w^\lambda)^{1-\beta_i} \\ \Leftrightarrow [1 - G(\phi_i^{*\lambda})] \frac{1}{\delta} \left\{ \frac{\bar{r}_i^\lambda}{\sigma} - f_i(s^\lambda)^{\beta_i} (w^\lambda)^{1-\beta_i} \right\} &= f_{ei}(s^\lambda)^{\beta_i} (w^\lambda)^{1-\beta_i} \\ \Leftrightarrow [1 - G(\phi_i^{*\lambda})] \frac{1}{\delta} \left\{ \frac{1}{\sigma} \left(\frac{\bar{\phi}_i}{\phi_i^{*\lambda}} \right)^{\sigma-1} \cdot r_i^\lambda(\phi_i^{*\lambda}) - f_i(s^\lambda)^{\beta_i} (w^\lambda)^{1-\beta_i} \right\} &= f_{ei}(s^\lambda)^{\beta_i} (w^\lambda)^{1-\beta_i} \\ \Leftrightarrow [1 - G(\phi_i^{*\lambda})] \frac{1}{\delta} \left\{ \left(\frac{\bar{\phi}_i}{\phi_i^{*\lambda}} \right)^{\sigma-1} - 1 \right\} f_i(s^\lambda)^{\beta_i} (w^\lambda)^{1-\beta_i} &= f_{ei}(s^\lambda)^{\beta_i} (w^\lambda)^{1-\beta_i} \\ \Leftrightarrow [1 - G(\phi_i^{*\lambda})] \frac{f_i}{\delta} \left\{ \frac{1}{1 - G(\phi_i^{*\lambda})} \int_{\phi_i^{*\lambda}}^{\infty} \left(\frac{\phi}{\phi_i^{*\lambda}} \right)^{\sigma-1} g(\phi) d\phi - 1 \right\} &= f_{ei} \end{aligned}$$

and thus Equation (12) follows.

2. Derivation of Equations (17) & (18):

Here I derive only Equation (17) for Home. Equation (18) for Foreign is derived analogously.

From Equation (13) for the optimal pricing of exported product, the revenue of an individual firm earned from the overseas market (export) is as follows:

$$r_{xi,\omega}^H(\phi) = \alpha_i Y^F \left(\frac{\tau_i (S^H)^{\beta_i} (w^H)^{1-\beta_i}}{\rho P_i^F \phi} \right)^{1-\sigma} \quad (\text{A.2})$$

From this and Equation (6), the ratio of the revenue earned by an exporter and that earned by a domestic producer in Home country is expressed as follows:

$$\frac{r_{xi}^H(\phi)}{r_i^H(\phi)} = \tau_i^{1-\sigma} \left(\frac{P_i^F}{P_i^H} \right)^{\sigma-1} \left(\frac{Y^F}{Y^H} \right) \quad (\text{A.3})$$

Equation (A.1) can be modified to the following equation, which implies that the ratio of two firms' productivities is a function of the ratio of the revenues that two firms earn *in the same (domestic) market*:

$$\frac{\phi'}{\phi} = \left(\frac{r_i(\phi')}{r_i(\phi)} \right)^{\frac{1}{\sigma-1}} \quad (\text{A.4})$$

Using Equations (A.3) and (A.4), we can express the ratio of the productivity cutoff for exporting to the cutoff for domestic production in Home as follows:

$$\begin{aligned} \frac{\phi_{xi}^{*H}}{\phi_i^{*H}} &= \left(\frac{r_i^H(\phi_{xi}^{*H})}{r_i^H(\phi_i^{*H})} \right)^{\frac{1}{\sigma-1}} \\ &= \left(\frac{r_{xi}^H(\phi_{xi}^{*H}) \cdot \tau_i^{\sigma-1} \left(\frac{P_i^H}{P_i^F} \right)^{\sigma-1} \left(\frac{Y^H}{Y^F} \right)}{r_i^H(\phi_i^{*H})} \right)^{\frac{1}{\sigma-1}} \\ &= \tau_i \left(\frac{r_{xi}^H(\phi_{xi}^{*H})}{r_i^H(\phi_i^{*H})} \right)^{\frac{1}{\sigma-1}} \cdot \left(\frac{P_i^H}{P_i^F} \right) \left(\frac{Y^H}{Y^F} \right)^{\frac{1}{\sigma-1}} \\ &= \tau_i \left(\frac{f_{xi}}{f_i} \right)^{\frac{1}{\sigma-1}} \left(\frac{P_i^H}{P_i^F} \right) \left(\frac{Y^H}{Y^F} \right)^{\frac{1}{\sigma-1}} \end{aligned}$$

The last equality is from the zero-profit condition in the domestic market (6) and the zero-profit condition in the export market (15). Equation (17) thus follows by defining the right-hand side of the last line of the equation above as Λ_i^H .

3. Derivation of Equation (21):

Note that, from Equation (7);

$$\begin{aligned}\bar{\pi}_i^H &= \frac{\bar{r}_i^H}{\sigma} - f_i(s^H)^{\beta_i} (w^H)^{1-\beta_i} \\ &= \frac{1}{\sigma} \left(\frac{\bar{\phi}_i^H}{\phi_i^{*H}} \right)^{\sigma-1} \cdot r_i^{*H} - f_i(s^H)^{\beta_i} (w^H)^{1-\beta_i} \\ &= \left[\left(\frac{\bar{\phi}_i^H}{\phi_i^{*H}} \right)^{\sigma-1} - 1 \right] \cdot f_i(s^H)^{\beta_i} (w^H)^{1-\beta_i}\end{aligned}$$

The second equality is derived using (A.1), and the third equality is from Equation (15).

Analogously;

$$\bar{\pi}_{xi}^H = \left[\left(\frac{\bar{\phi}_{xi}^H}{\phi_{xi}^{*H}} \right)^{\sigma-1} - 1 \right] \cdot f_{xi}(s^H)^{\beta_i} (w^H)^{1-\beta_i}.$$

Substituting these equations for the average profit levels, as well as the average productivity

levels defined as $\bar{\phi}_i^{\lambda}(\phi_i^{*\lambda}) = \left[\frac{1}{1 - G(\phi_i^{*\lambda})} \int_{\phi_i^{*\lambda}}^{\infty} \phi^{\sigma-1} g(\phi) d\phi \right]^{\frac{1}{\sigma-1}}$ and

$\bar{\phi}_{xi}^{\lambda}(\phi_{xi}^{*\lambda}) = \left[\frac{1}{1 - G(\phi_{xi}^{*\lambda})} \int_{\phi_{xi}^{*\lambda}}^{\infty} \phi^{\sigma-1} g(\phi) d\phi \right]^{\frac{1}{\sigma-1}}$, yields:

$$\begin{aligned}
& \left[\frac{f_i}{\delta} \int_{\phi_i^{*H}}^{\infty} \left\{ \left(\frac{\phi}{\phi_i^{*H}} \right)^{\sigma-1} - 1 \right\} g(\phi) d\phi \right] \cdot (s^H)^{\beta_i} (w^H)^{1-\beta_i} + \left[\frac{f_{xi}}{\delta} \int_{\phi_{xi}^{*H}}^{\infty} \left\{ \left(\frac{\phi}{\phi_{xi}^{*H}} \right)^{\sigma-1} - 1 \right\} g(\phi) d\phi \right] \cdot (s^H)^{\beta_i} (w^H)^{1-\beta_i} \\
& = f_{ei} (s^H)^{\beta_i} (w^H)^{1-\beta_i}
\end{aligned}$$

, which Equation (21) follows by canceling out the term $(s^H)^{\beta_i} (w^H)^{1-\beta_i}$ on the both sides.

4. Relative Factor Prices under Costly Trade:

Here I demonstrate that in equilibrium the relative prices of the two production factors (S and U) is not equalized in our framework of costly trade. The wage for skilled labor relative to the that for unskilled labor will be lower in Home, where skilled labor is relatively more abundant, than in Foreign; i.e., $\frac{s^H}{w^H} < \frac{s^F}{w^F}$.

First, note that autarky and free trade are the two extreme cases, or limits, of the costly trade.

That is, the former is the limit with infinitely large trade costs ($f_{xi} \rightarrow \infty, \tau_i \rightarrow \infty$), and the

latter is the limit with no additional costs for trade ($f_{xi} \rightarrow 0, \tau_i \rightarrow 1$). The equilibrium

relative factor price under costly trade will fall in the range between those in these two limit

cases (i.e., $\frac{s^H}{w^H} < \frac{s^F}{w^F}$). I will thus show how the relative factor prices in the two countries

will be in these two limit cases.

(1) Autarky

Since the production function (4) has a Cobb-Douglas form, the optimal allocation of the two factors in each industry is such that the total payment to each factor is proportional to the total revenue, which equals the total expenditure, in the industry. That is, WLOG in Home,

$$S_i^H = \left(\frac{\beta_i}{s^H} \right) R_i^H = \left(\frac{\beta_i}{s^H} \right) \alpha_i Y^H \quad (\text{A.5})$$

$$L_i^H = \left(\frac{1 - \beta_i}{w^H} \right) R_i^H = \left(\frac{1 - \beta_i}{w^H} \right) \alpha_i Y^H \quad (\text{A.6})$$

where R_i^H is the total revenue in Industry i in Home, which is equal to the total industry expenditure in equilibrium. The industry expenditure is proportional to the national income due to the Cobb-Douglas utility function (1) (i.e., $R_i^H = \alpha_i Y^H$).

Inelastic supply of each factor equals the sum of that factor allocated to each industry, that is;

$$\bar{S}^H = \sum_i S_i^H = \frac{Y^H}{s^H} \sum_i \alpha_i \beta_i \Leftrightarrow s^H \bar{S}^H = Y^H \sum_i \alpha_i \beta_i \quad (\text{A.7})$$

$$\bar{U}^H = \sum_i U_i^H = \frac{Y^H}{w^H} \sum_i \alpha_i (1 - \beta_i) \Leftrightarrow w^H \bar{U}^H = Y^H \sum_i \alpha_i (1 - \beta_i) \quad (\text{A.8})$$

Dividing (A.7) by (A.8) in both sides yields the following equation for Home:

$$\frac{s^H \bar{S}^H}{w^H \bar{U}^H} = \frac{\sum_i \alpha_i \beta_i}{\sum_i \alpha_i (1 - \beta_i)} \Leftrightarrow \frac{s^H}{w^H} = \left(\frac{\sum_i \alpha_i \beta_i}{\sum_i \alpha_i (1 - \beta_i)} \right) \cdot \left(\frac{\bar{U}^H}{\bar{S}^H} \right) \quad (\text{A.9})$$

Analogously, for Foreign,

$$\frac{s^H}{w^H} = \left(\frac{\sum_i \alpha_i \beta_i}{\sum_i \alpha_i (1 - \beta_i)} \right) \cdot \left(\frac{\bar{U}^H}{\bar{S}^H} \right) \quad (\text{A.9}')$$

Since consumers share the identical preference and the Cobb-Douglas cost share of each production factor is common across countries within each industry (i.e., the parameters α_i and β_i are common across countries), the first term of the product in the right-hand side of

Equations (A.9) and (A.9') is the same for both countries. Hence, the relative factor price $\frac{s}{w}$

in each country is determined by the ratio of the two factors that the country is endowed with,

$\frac{\bar{S}}{\bar{U}}$. Since $\frac{\bar{S}^H}{\bar{U}^H} > \frac{\bar{S}^F}{\bar{U}^F}$ by assumption, (A.9) and (A.9') imply that $\frac{s^H}{w^H} < \frac{s^F}{w^F}$ in the autarky

equilibrium.

(2) Free Trade

Here I focus on the case with FPE. We can identify the equilibrium relative factor price with FPE by solving for the problem of the integrated world economy, which is characterized by Equations (A.5) through (A.9) in the autarky case described above, but omitting the country

script. The common relative factor price $\frac{s}{w}$ is determined by the world relative factor supply

$\frac{\bar{S}}{\bar{U}} = \frac{\bar{S}^H + \bar{S}^F}{\bar{U}^H + \bar{U}^F}$. Hence, in the free-trade equilibrium with FPE, $\frac{s^H}{w^H} = \frac{s^F}{w^F}$.⁵⁸

5. Proof of Proposition:

WLOG, in this proof I focus on the skill-abundant Home country.

The probability of a domestic producer being an exporter, χ_i^H , is determined by the ratio between the two productivity cutoffs, the one for domestic production ϕ_i^{*H} and the one for exporting ϕ_{xi}^{*H} . Since, as in Equation (17), the ratio between these two productivity cutoffs

$(\frac{\phi_{xi}^{*H}}{\phi_i^{*H}} = \Lambda_i^H = \tau_i \left(\frac{P_i^H}{P_i^F} \right) \left(\frac{Y^H}{Y^F} \cdot \frac{f_{xi}}{f_i} \right)^{\frac{1}{\sigma-1}})$ depends upon the Home and Foreign industry price

indexes (P_i^H and P_i^F), I take the following proof strategy:

⁵⁸ We can show that there exist the optimal allocations of the two factors to each industry in each country with FPE, although the allocations are not unique (Melvin's indeterminacy). The authors can provide the proof upon request.

- (i) I first show that the relative industry price index (Home to Foreign) is smaller for an industry in which the skill-abundant Home has stronger comparative advantage (i.e.,

$$\frac{P_i^H}{P_i^F} < \frac{P_j^H}{P_j^F} \text{ for } i \neq j \text{ such that } \beta_i > \beta_j);$$

- (ii) I next demonstrate that (i) implies that the ratio between the two productivity cutoffs is smaller in an industry in which the country has stronger comparative advantage

$$(\text{i.e., } \frac{\phi_{xi}^{*H}}{\phi_i^{*H}} < \frac{\phi_{xj}^{*H}}{\phi_j^{*H}} \text{ for } i \neq j \text{ such that } \beta_i > \beta_j);$$

and

- (iii) I then use the results in (ii) and the relationship between the relative factor prices in the two countries in equilibrium, which has been derived in 4. in this appendix, to compare across industries the probability of the Home active firms to be an exporter, χ_i^H and χ_j^H .

(i) Relative industry price index in two countries

To demonstrate that $\frac{P_i^H}{P_i^F} < \frac{P_j^H}{P_j^F}$ for $i \neq j$ such that $\beta_i > \beta_j$, here I apply a similar logic to the

one that I have used in above-mentioned 4. to show the relative factor prices in the costly-

trade equilibrium ($\frac{S^H}{W^H} < \frac{S^F}{W^F}$). The relative industry price index in the costly-trade

equilibrium is as follows:

$$\frac{P_i^H}{P_i^F} = \frac{[M_i^H (p_i^H (\bar{\phi}_i^H))^{1-\sigma} + \chi_i^F \cdot M_i^F \cdot \tau_i^{1-\sigma} (p_i^F (\bar{\phi}_{xi}^F))^{1-\sigma}]^{\frac{1}{1-\sigma}}}{[M_i^F (p_i^F (\bar{\phi}_i^F))^{1-\sigma} + \chi_i^H \cdot M_i^H \cdot \tau_i^{1-\sigma} (p_i^H (\bar{\phi}_{xi}^H))^{1-\sigma}]^{\frac{1}{1-\sigma}}} \quad (\text{A.10})$$

Since the autarky equilibrium and the free-trade FPE equilibrium are the two extreme or limit cases, the relative price index in the costly trade equilibrium falls between the one in the autarky equilibrium and the one in the free-trade FPE equilibrium.

In autarky, which is characterized by $\tau_i = \infty$ and $f_{xi} = \infty$, no firms will be exporters ($\chi_i = 0$ in each country). Therefore, Equation (A.10) is now as follows:

$$\frac{P_i^H}{P_i^F} = \frac{(M_i^H)^{\frac{1}{1-\sigma}} \cdot p_i^H(\bar{\phi}_i^H)}{(M_i^F)^{\frac{1}{1-\sigma}} \cdot p_i^F(\bar{\phi}_i^F)} = \left(\frac{M_i^H}{M_i^F} \right)^{\frac{1}{1-\sigma}} \left(\frac{p_i^H(\bar{\phi}_i^H)}{p_i^F(\bar{\phi}_i^F)} \right) \quad (\text{A.11})$$

Since $M_i = R_i / r_i(\bar{\phi}_i)$ and $R_i = \alpha_i Y$ for each country in the autarky equilibrium, Equation (A.11) yields the following equation;

$$\frac{P_i^H}{P_i^F} = \left(\frac{Y^H}{Y^F} \right)^{\frac{1}{1-\sigma}} \left(\frac{r_i^F(\bar{\phi}_i^F)}{r_i^H(\bar{\phi}_i^H)} \right)^{\frac{1}{1-\sigma}} \left(\frac{p_i^H(\bar{\phi}_i^H)}{p_i^F(\bar{\phi}_i^F)} \right) \quad (\text{A.12})$$

Note that the optimal pricing Equation (5) implies that the ratio of the prices charged by two firms with different productivity *in the same market* can be expressed as the ratio of the two productivities, i.e.;

$$p_i(\phi') = \left(\frac{\phi}{\phi'} \right) \cdot p_i(\phi)$$

Using this equation and Equation (A.1), as well as the optima pricing (5) and the zero-profit condition (9), Equation (A.12) can be expressed as follows:

$$\frac{P_i^H}{P_i^F} = \left(\frac{Y^H}{Y^F} \right)^{\frac{1}{1-\sigma}} \left(\frac{\left(\frac{\bar{\phi}_i^F}{\bar{\phi}_i^{*F}} \right)^{\sigma-1} (s^F)^{\beta_i} (w^F)^{1-\beta_i}}{\left(\frac{\bar{\phi}_i^H}{\bar{\phi}_i^{*H}} \right)^{\sigma-1} (s^H)^{\beta_i} (w^H)^{1-\beta_i}} \right)^{\frac{1}{1-\sigma}} \left(\frac{\left(\frac{\bar{\phi}_i^H}{\bar{\phi}_i^{*H}} \right)^{\sigma-1} \frac{(s^H)^{\beta_i} (w^H)^{1-\beta_i}}{\bar{\phi}_i^{*H}}}{\left(\frac{\bar{\phi}_i^F}{\bar{\phi}_i^{*F}} \right)^{\sigma-1} \frac{(s^F)^{\beta_i} (w^F)^{1-\beta_i}}{\bar{\phi}_i^{*F}}} \right) \quad (\text{A.13})$$

Note that the productivity cutoff for each country, ϕ_i^* , is determined by the free-entry condition (12), which is common for the two countries. Therefore, $\phi_i^{*H} = \phi_i^{*F}$, and accordingly, $\bar{\phi}_i^H = \bar{\phi}_i^F$ since the productivity distribution is also common across countries. These imply that $\frac{\bar{\phi}_i^H}{\phi_i^{*H}} = \frac{\bar{\phi}_i^F}{\phi_i^{*F}}$. Hence, from Equation (A.13) we obtain the following:

$$\begin{aligned} \frac{P_i^H}{P_i^F} &= \left(\frac{Y^H}{Y^F} \right)^{\frac{1}{1-\sigma}} \cdot \left\{ \left(\frac{s^F}{s^H} \right)^{\beta_i} \left(\frac{w^F}{w^H} \right)^{1-\beta_i} \right\}^{\frac{1}{1-\sigma}} \\ \Leftrightarrow \frac{P_i^H}{P_i^F} &= \left(\frac{Y^H}{Y^F} \right)^{\frac{1}{1-\sigma}} \cdot \left\{ \left(\frac{s^H / w^H}{s^F / w^F} \right)^{\beta_i} \left(\frac{w^H}{w^F} \right) \right\}^{\frac{\sigma}{\sigma-1}} \end{aligned} \quad (\text{A.14})$$

Analogously;

$$\frac{P_j^H}{P_j^F} = \left(\frac{Y^H}{Y^F} \right)^{\frac{1}{1-\sigma}} \cdot \left\{ \left(\frac{s^H / w^H}{s^F / w^F} \right)^{\beta_j} \left(\frac{w^H}{w^F} \right) \right\}^{\frac{\sigma}{\sigma-1}} \quad (\text{A.15})$$

It has been shown in 4.(1) above that $\frac{s^H}{w^H} < \frac{s^F}{w^F}$ in autarky. Therefore, since $\beta_i > \beta_j$, it follows

that $\frac{P_i^H}{P_i^F} < \frac{P_j^H}{P_j^F}$ in the autarky equilibrium.

Next, consider the free-trade equilibrium, which is characterized by $\tau_i = 1$ and $f_{xi} = 0$. Since all domestically active firms will export, $\chi_i^\lambda = 1$ in each country λ . Furthermore, with FPE, firms in the two countries will charge the same price for both domestic sales and export if their productivities are the same, $p_i^H(\bar{\phi}_i^H) = p_{xi}^H(\bar{\phi}_{xi}^H) = p_i^F(\bar{\phi}_i^F) = p_{xi}^F(\bar{\phi}_{xi}^F)$ (the average productivity is the same across countries since it is determined by the common free-entry condition (12)). Hence, Equation (A.10) yields:

$$\frac{P_i^H}{P_i^F} = \frac{(M_i^H + M_i^F)^{\frac{1}{1-\sigma}}}{(M_i^H + M_i^F)^{\frac{1}{1-\sigma}}} = 1$$

Therefore, under costly trade, which is the intermediate case of the two extremes shown

above, $\frac{P_i^H}{P_i^F} < \frac{P_j^H}{P_j^F}$ for $i \neq j$ such that $\beta_i > \beta_j$ in equilibrium.

(ii) *Ratio between the export cutoff productivity and the domestic production cutoff productivity*

From Equations (17) and (18);

$$\frac{\phi_{xi}^{*H}}{\phi_i^{*H}} = \Lambda_i^H = \tau_i \left(\frac{P_i^H}{P_i^F} \right) \left(\frac{Y^H}{Y^F} \cdot \frac{f_{xi}}{f_i} \right)^{\frac{1}{\sigma-1}}$$

$$\frac{\phi_{xj}^{*H}}{\phi_j^{*H}} = \Lambda_j^H = \tau_j \left(\frac{P_j^H}{P_j^F} \right) \left(\frac{Y^H}{Y^F} \cdot \frac{f_{xj}}{f_j} \right)^{\frac{1}{\sigma-1}}$$

Suppose $\tau_i = \tau_j = \tau$, $f_i = f_j = f$, and $f_{xi} = f_{xj} = f_x$. Then, from the result in (i) above, these two equations imply that:

$$\text{If } \beta_i > \beta_j, \text{ then } (1 <) \Lambda_i^H < \Lambda_j^H \Leftrightarrow (1 <) \frac{\phi_{xi}^{*H}}{\phi_i^{*H}} < \frac{\phi_{xj}^{*H}}{\phi_j^{*H}}. \quad (\text{A.16})$$

(iii) *Cross-industry comparison of the probability of exporting*

According to Assumption, $G(\phi_i) = 1 - \left(\frac{\phi_i}{\phi_i} \right)^k$, $k > 2\sigma$. Then,

$$\chi_i^H = \frac{1 - G(\phi_{xi}^{*H})}{1 - G(\phi_i^{*H})} = \frac{(\phi_i / \phi_{xi}^{*H})^k}{(\phi_i / \phi_i^{*H})^k} = \left(\frac{\phi_i^{*H}}{\phi_{xi}^{*H}} \right)^k = \left(\frac{\phi_{xi}^{*H}}{\phi_i^{*H}} \right)^{-k},$$

$$\chi_j^H = \frac{1 - G(\phi_{xj}^{*H})}{1 - G(\phi_j^{*H})} = \left(\frac{\phi_{xj}^{*H}}{\phi_j^{*H}} \right)^{-k}.$$

Therefore, from (A.16),

$$\text{If } \beta_i > \beta_j, \text{ then } \frac{\phi_{xi}^{*H}}{\phi_i^{*H}} < \frac{\phi_{xj}^{*H}}{\phi_j^{*H}} \Leftrightarrow \left(\frac{\phi_{xi}^{*H}}{\phi_i^{*H}} \right)^{-k} > \left(\frac{\phi_{xj}^{*H}}{\phi_j^{*H}} \right)^{-k} \Leftrightarrow \chi_i^H > \chi_j^H.$$

Since this holds for any industry pair i and j ($i, j = 1, 2, \dots, N$) that satisfies $\beta_i > \beta_j$, the

Proposition thus follows.

Appendix B

This appendix examines the potential impacts of sample truncation in manufacturing census data on the result of the empirical analysis in this paper. As described in Section 3, the manufacturing census of each country omits firms whose employment is less than the threshold level (ten employees for the Chile and Colombia, and 20 employees for India; the U.S. census also excludes small firms: see the General Summary of the U.S. Census of Manufactures for the details). The omission of small firms might potentially cause the overestimation of exporter fraction, since the number of domestic firms in the data, which is the denominator of the fraction, does not count such small firms.⁵⁹ This overestimation of the exporter fraction might occur for all industries, but if the degree of the overestimation would differ systematically in relation to the factor intensity (or more specifically, the skill intensity) of the industries, it could result in the biased estimation of a correlation between the exporter fractions and the industry skill intensities. In what follows, I examine whether such estimation bias could crucially affect, or mislead, the result of the empirical findings presented in Section 4.

From Theory

The theoretical model presented in Section 2 suggests that the minimum productivity level required for domestic production is lower in comparative-disadvantage industries and higher in comparative-advantage industries. This implies that comparative-*disadvantage*

⁵⁹ The omission of small firms might also affect the numerator of the fraction, if some of these small firms export. However, Bernard and Jensen (1995) and other studies have found that exporters are significantly larger than non-exporters in terms of employment size, and it is expected that, even though the small firms include exporters, the fraction of exporters in these small firms is (significantly) smaller than the exporter fraction in all firms. The exporter fraction observed in the census data might thus still overestimate the fraction in the population.

industries contain more small-size firms (in terms of employment) compared to comparative-advantage industries.⁶⁰ Therefore, if the sample of firms is truncated at the same threshold employment level for all industries, the number of small domestic firms omitted from the sample is larger in comparative-*dis*advantage industries, and thus the exporter fraction is more overestimated in the sample for comparative-*dis*advantage industries. This pattern of overestimation implies that the predicted relationship between the exporter fraction and comparative advantage is weaker in the sample than in the population. In other words, for a more skill-abundant country (e.g., the United States) the correlation between the exporter fractions and industry skill intensities in the sample is estimated to be *less positive* than how it should be in the population, and for a less skill-abundant country (e.g., India) the correlation in the sample is estimated to be *less negative* than how it should be in the population. This suggest that the quasi-Heckscher-Ohlin pattern of the exporter fraction, which is found to be significant in the empirical analysis in Section 4, should be even stronger in the population of firms that includes small firms.

From Data

Recall Equation (23) for individual country analysis:

$$ex_share_i = \gamma + \theta \cdot skill_i + \varepsilon_i \quad (23)$$

Since ex_share_i on the left-hand side is the ratio of the number of exporters in a sample to the number of domestic producers in the sample, this equation can also be expressed as follows:

⁶⁰ The present model implies that a firm with a lower productivity level is smaller in both sales size and employment size. In addition, with the assumption of a Pareto distribution for firms' productivity, both sales sizes and employment sizes of firms are also distributed in a Pareto distribution. The proof can be provided upon request.

$$\left(\frac{EX_i}{DOM_i} \right) \cdot \left(\frac{1 - ex_i / EX_i}{1 - dom_i / DOM_i} \right) = \gamma + \theta \cdot skill_i + \varepsilon_i \quad (B.1)$$

where EX_i , ex_i , DOM_i , and dom_i denote the numbers of exporters in a firm population, exporters in small firms omitted from the sample, domestic producers in the population, and domestic producers in the small firms in Industry i , respectively. Hence, if the second element of the left-hand side of Equation (B.1), $\frac{1 - ex_i / EX_i}{1 - dom_i / DOM_i}$, would be positively (negatively) correlated to the industry skill intensity $skill_i$, the estimation of Equation (23) would provide a positive (negative) estimate for the coefficient θ even though the exporter fraction in the population is not correlated to the skill intensity at all. Or, at least, a regression would overestimate or underestimate the correlation in the population.⁶¹

To check whether such spurious correlation or the estimation bias is crucial in the present empirical analysis, I examine the cross-industry correlation for the term

$$\frac{1 - ex_i / EX_i}{1 - dom_i / DOM_i} \text{ and the skill intensity term } skill_i \text{ for Chile and Colombia, for which data are}$$

available at the firm level.⁶² Since in the data I cannot observe omitted small firms with less than ten employees, I measure ex_i and dom_i using a group of the smallest firms in the data for each country, i.e., firms with (more than 10 and) less than 20 workers; and measure the population counterparts EX_i and DOM_i from all firms included in the data. The variables are for 25 three-digit ISIC industries and of the average over the years 1990 through 96 for Chile, and 1981-91 for Colombia.

⁶¹ The empirical result could be misled if overestimation would be the case for a positive coefficient estimate $\hat{\theta}$, or if underestimate would be the case for a negative coefficient estimate.

⁶² The data for India and the United States do not have sufficient firm-level information for the same examination.

The estimated correlation between $\frac{1 - ex_i / EX_i}{1 - dom_i / DOM_i}$ and $skill_i$ for Chile is -0.255 with the p-value of 0.219. This implies that the coefficient θ estimated in Section 4, which is positive and significant, might be underestimated (but not significantly) in the sample, and therefore the population coefficient could be even more positive.⁶³ For Colombia, the estimated correlation between the two terms is almost zero (the correlation coefficient is -0.085 with the p-value of 0.686). These results suggest that sample truncation should not cause estimation bias and thus the empirical finding in Section 4 should be valid.

⁶³ Note that this is consistent with what the theoretical model suggests.

Appendix C

This appendix performs an exercise to examine from a pure empirical perspective whether the relative factor abundance of a country and the relative factor intensity of an industry have a significant influence on the fraction of exporters among domestic firms in that industry in that country. For this purpose, I estimate a variant of Equation (26) using a larger pooled dataset that is composed as follows:

- An observation is for one country, one industry, and one year. That is, data for seven years (1990-1996) are used for Chile, and data for eleven years (1981-1991) are used for Colombia. The data for India and the United States are for a single year (1998 for India, 1992 for the U.S.).
- Industry skill intensity is allowed to vary across countries and years (i.e., a standard Heckscher-Ohlin assumption is relaxed).⁶⁴
- Factor abundance in each country is assumed to be invariant over periods, and measured using the data provided by Hall and Jones (1999).
- For every country, the manufacturing industries are classified according to the two-digit 1987 U.S. SIC; i.e., there are 17 observations⁶⁵ for each country in each year.

This way I can increase the number of observations in the dataset to 340.

The equation is estimated by OLS including various combinations of dummies for one or more groups (dummies for countries, industries, and/or years). Hence, the regression equation is as follows:

⁶⁴ Schott (2003) shows that in reality different countries employ different factor mixes for production in the same industry classified according to the three-digit ISIC.

⁶⁵ Tobacco, petroleum and coal, and miscellaneous industry categories are excluded.

$$ex_share_{ict} = \theta_1 \cdot skill_{ict} + \theta_2 \cdot skill_{ict} \cdot \log(S/U)_c + (\eta_i + \mu_c + \nu_t + \varepsilon_{ic}) \quad (C.1)$$

where η_i , μ_c , and ν_t denote industry-specific, country-specific, and year-specific intercepts, respectively.

The results of the regressions are shown in Tables C1 through C8. With any combination of the dummies (or with no dummies), the estimate of the coefficient of interest, θ_2 , is positive and significant at the 5% level or better. Two exceptions are (i) when only country-specific dummies are included, and (ii) both country-specific dummies and year-specific dummies are simultaneously included. However, even in these cases, the coefficient estimate is positive and large (above 0.8) and the p-value of the estimate is not very far from 0.1. These results indicate that the data strongly suggest an empirical relationship between comparative advantage and exporter selection.

Appendix D

This appendix describes how the alternative measure of industry skill intensity (or the skilled-worker cost shares of an industry) that is used in Subsection 4.(3) is computed following Morrow (2008). For the details of Morrow's calculation, see his paper.

Morrow obtains the data on wages, educational attainment, and ages of workers from the March U.S. Current Population Survey for the years 1988-92. These data are used for a Mincerian (log of) wage regression. He groups the educational attainment of workers into the following four categories: 0-11 grades of school completed, 12th grade completed, 1-3 years of college, and 4 or more years of college. The equation for his Mincerian regression is the following:

$$\log(w_{it}) = \alpha_0 + \alpha_1 \cdot age_{it} + \alpha_2 \cdot age_{it}^2 + \beta_{12th} \cdot D_{12th} + \beta_{college1-3} \cdot D_{college1-3} + \beta_{college4+} \cdot D_{college4+} + \gamma_t + \varepsilon_{it}$$

where i indexes a worker, t indexes time. $D_{12th} = 1$ if the worker has completed 12th grade, $D_{college1-3} = 1$ if the worker has attained 1-3 years of college education, and $D_{college4+} = 1$ if the worker has attained 4 or more years of college education. γ_t is time-specific intercepts. The coefficient for each education-group dummy (β) indicates the wage for a worker in that education group relative to the wage for a worker in the benchmark (the lowest) education group in logarithm, when the two workers differ only in their educational attainment. That is; $w_{edu} / w_0 = \exp(\beta_{edu})$ where edu is some education group and 0 denotes the benchmark education group. He reports the following coefficient estimates for the three education-group dummies:

β_{12th}	$\beta_{college1-3}$	$\beta_{college4+}$
0.2939	0.4755	0.8128

He also reports the share of workers in each education category, as well as the total number of workers reported in the Current Population Survey, for the 25 manufacturing industries classified according to the three-digit ISIC. Using these numbers, I calculate the share of workers in each education category for the 17 manufacturing industries classified according to the two-digit U.S. SIC, using the concordance presented in Table 9. The obtained shares of workers in the three education categories in the 17 industries are shown in the table below.

Shares of Workers in Different Education Categories in Total Employment:
for 17 Two-digit 1987 U.S. SIC Manufacturing Industries

SIC	Total No. Workers	12th Grade Completion or Less	1-3 Years of College	4+ Years of College
20	6,427	0.714	0.174	0.111
22	3,059	0.798	0.127	0.075
23	3,369	0.834	0.110	0.056
24	1,891	0.757	0.162	0.081
25	2,118	0.777	0.145	0.077
26	2,358	0.652	0.212	0.136
27	6,132	0.501	0.246	0.253
28	3,773	0.447	0.230	0.323
30	3,068	0.691	0.189	0.121
31	601	0.800	0.110	0.090
32	1,944	0.703	0.176	0.121
33	2,400	0.691	0.205	0.105
34	3,911	0.688	0.201	0.110
35	3,179	0.624	0.243	0.133
36	10,699	0.501	0.243	0.256
37	7,501	0.553	0.251	0.196
38	2,225	0.493	0.246	0.261

Source: Author's calculation from Morrow (2008).

From these data, I calculate the cost share of skilled workers in each two-digit U.S. SIC manufacturing industry. I define skilled labor by workers with one or more years of college education (i.e., workers in the highest two education categories). While Morrow's benchmark

education category is 0-11 grades of schooling, he does not report the share of workers in this category. Instead, he reports the share of workers with high school education or less, which combines the lowest two education categories of workers (0-11 grades and 12th grade). Hence, I use the group of workers with 12th or lower grade of education as my benchmark category, and compute the skilled-labor cost share in each industry as follows:

$$\begin{aligned}
 skill_i &= \frac{(wage_{college4+} / wage_{0-12th}) \cdot R_{college4+} + (wage_{college1-3} / wage_{0-12th}) \cdot R_{college1-3}}{(wage_{college4+} / wage_{0-12th}) \cdot R_{college4+} + (wage_{college1-3} / wage_{0-12th}) \cdot R_{college1-3} + R_{0-12th}} \\
 &= \frac{\exp(\beta_{college4+} - \beta_{12th}) \cdot R_{college4+} + \exp(\beta_{college1-3} - \beta_{12th}) \cdot R_{college1-3}}{\exp(\beta_{college4+} - \beta_{12th}) \cdot R_{college4+} + \exp(\beta_{college1-3} - \beta_{12th}) \cdot R_{college1-3} + R_{0-12th}}
 \end{aligned}$$

where R_{0-12th} is the share of workers with 12th or less grade, $R_{college1-3}$ is the share of workers with 1-3 years of college, and $R_{college4+}$ is the share of workers with 4 or more years of college.

The calculated skilled-labor cost shares in the 17 manufacturing industries are reported in Table 12.

Table 1. Fractions of Exporting Firms in Manufacturing Industries (2-digit U.S. SIC): Chile, Colombia, India, and the United States

		Chile (avg. 1990-96)				Colombia (avg. 1981-91)				India (FY 1997/98)				United States (1992)			
SIC	Industry	# Active Firms (a)	# Exporters (b)	Ratio (b)/(a)		# Active Firms (a)	# Exporters (b)	Ratio (b)/(a)		# Active Firms (a)	# Exporters (b)	Ratio (b)/(a)		# Active Firms (a)	# Exporters (b)	Ratio (b)/(a)	
20	Food and kindred products	1,523	301	19.8%		1,332	98	7.4%		4,690	353	7.5%		20,641	4,563	22.1%	
21	Tobacco products	3	2	69.6%		15	3	23.5%		600	27	4.5%		114	67	58.8%	
22	Textile mill products	358	77	21.6%		466	65	13.9%		3,489	615	17.6%		5,868	1,613	27.5%	
23	Apparel and other textile products	322	44	13.5%		983	87	8.9%		644	349	54.2%		22,935	2,801	12.2%	
24	Lumber and wood products	355	83	23.3%		179	12	6.8%		718	16	2.2%		35,245	3,266	9.3%	
25	Furniture and fixtures	144	19	13.1%		202	9	4.5%		111	3	2.7%		11,620	2,058	17.7%	
26	Paper and allied products	74	27	36.3%		142	21	14.6%		680	54	7.9%		6,401	1,840	28.7%	
27	Printing and publishing	210	22	10.3%		358	31	8.7%		722	29	4.0%		65,349	4,495	6.9%	
28	Chemicals and allied products	257	116	45.0%		421	102	24.3%		2,314	513	22.2%		11,982	5,502	45.9%	
29	Petroleum and coal products	22	11	50.0%		27	4	14.4%		262	14	5.3%		1,961	416	21.2%	
30	Rubber and miscellaneous plastics products	306	76	24.9%		390	62	16.0%		1,344	158	11.8%		15,819	5,806	36.7%	
31	Leather and leather products	209	45	21.8%		356	68	19.2%		373	170	45.6%		2,032	677	33.3%	
32	Stone, clay, and glass products	188	28	15.0%		393	42	10.6%		2,239	197	8.8%		16,001	2,116	13.2%	
33	Primary metal industries	65	31	48.0%		93	11	11.9%		1,534	195	12.7%		6,500	2,139	32.9%	
34	Fabricated metal products	405	57	14.1%		566	68	11.9%		1,312	111	8.5%		36,360	8,211	22.6%	
35	Industrial machinery and equipment	172	28	16.6%		316	59	18.7%		1,933	341	17.6%		53,849	13,990	26.0%	
36	Electronic and other electric equipment	59	17	28.2%		198	37	18.7%		1,425	246	17.3%		16,890	8,306	49.2%	
37	Transportation equipment	105	18	17.1%		226	27	12.1%		1,068	192	18.0%		11,249	3,711	33.0%	
38	Instruments and related products	19	6	33.6%		65	16	25.1%		284	69	24.3%		11,331	6,716	59.3%	
39	Miscellaneous manufacturing industries	63	11	16.7%		157	35	22.0%		385	90	23.4%		16,998	4,260	25.1%	
Total		4,859	1,019	21.0%		6,886	858	12.5%		26,127	3,742	14.3%		369,145	82,553	22.4%	

Sources: Author's calculation from the data of manufacturing census of the countries.

Table 2a: Human Capital to Labor Ratio (H/L)

	H/L (in logarithm)	Percentile	Rank
Chile	0.783	73	37
Colombia	0.590	36	61
India	0.409	24	89
United States	1.198	95	2
Mean	0.671		
Min	0.122		
25%	0.414		
Median	0.739		
75%	0.791		
Max	1.215		
No. of countries			127

Note: The summary statistics, ranks and percentile ranks are among 127 countries that are covered in the source data. All the numbers are based on the statistics weighted by the amount of labor (L) reported in the source data.

Source: Hall and Jones (1999)

Table 2b: Tertiary Education Completion in Total Population over Age 15

	1985			1990			1995		
	[%]	(rank)		[%]	(rank)		[%]	(rank)	
Chile	4.1%	[81]	(24)	5.0%	[81]	(29)	6.1%	[80]	(29)
Colombia	2.3%	[70]	(45)	3.2%	[72]	(44)	3.7%	[70]	(47)
India	1.2%	[45]	(60)	1.7%	[45]	(58)	2.0%	[44]	(60)
United States	15.4%	[94]	(1)	21.8%	[94]	(1)	22.5%	[94]	(1)
Mean	2.86%			3.79%			4.35%		
Min	0.0%			0.0%			0.1%		
25%	0.7%			1.4%			1.8%		
Median	1.2%			1.7%			2.0%		
75%	2.6%			3.5%			4.0%		
Max	15.4%			21.8%			22.5%		
No. of Countries			103			103			103

Note: The summary statistics, ranks and percentile ranks are among 103 countries that are covered in the source data. All the numbers are based on the statistics weighted by the population over age 15.

Sources: Barro and Lee (2000) for educational attainment; World Bank (2006) for population.

Table 3: Individual Country Regression: Chile

Dependent variable = <i>exporter share_i</i>	
Coef. for <i>skill_i</i> (θ)	0.634** (0.299)
Intercept (γ)	0.087 (0.092)
No. of observations	25
R ²	0.16

Notes: The observations are for 25 three-digit ISIC industries excluding 314 (tobacco products), 353 (petroleum refineries), 354 (misc. petroleum and coal products), and 390 (other manufacturing products). The standard errors are in parentheses.
 * indicates that the coefficient estimate is significant at the 10% level;
 ** indicates that the coefficient estimate is significant at the 5% level; and
 *** indicates that the coefficient estimate is significant at the 1% level.

Table 4: Individual Country Regression: Colombia

Dependent variable = <i>exporter share_i</i>	
Coef. for <i>skill_i</i> (θ)	-0.091 (0.217)
Intercept (γ)	0.180** (0.068)
No. of observations	25
R ²	0.01

Notes: The observations are for 25 three-digit ISIC industries excluding 314 (tobacco products), 353 (petroleum refineries), 354 (misc. petroleum and coal products), and 390 (other manufacturing products). The standard errors are in parentheses.
 * indicates that the coefficient estimate is significant at the 10% level;
 ** indicates that the coefficient estimate is significant at the 5% level; and
 *** indicates that the coefficient estimate is significant at the 1% level.

Table 5: Individual Country Regression: India

Dependent variable = $exporter\ share_i$	
Coef. for $skill_i (\theta)$	-0.865* (0.448)
Intercept (γ)	0.388*** (0.121)
No. of observations	25
R^2	0.12

Notes: The observations are for 25 three-digit ISIC industries excluding 314 (tobacco products), 353 (petroleum refineries), 354 (misc. petroleum and coal products), and 390 (other manufacturing products).
The standard errors are in parentheses.
* indicates that the coefficient estimate is significant at the 10% level;
** indicates that the coefficient estimate is significant at the 5% level; and
*** indicates that the coefficient estimate is significant at the 1% level.

Table 6: Comparison of Estimated Coefficients for Industry Skill Intensity among 3 Countries (with 25 three-digit ISIC manufacturing industries)

Dependent variable = $exporter\ share_i$	Chile	Colombia	India
Coef. for $skill_i (\theta)$	0.634** (0.299)	-0.091 (0.217)	-0.865* (0.448)
$\log(H/L)$	0.783	0.590	0.409

Notes: The coefficient for each country is estimated with 25 three-digit ISIC industries excluding 314 (tobacco products), 353 (petroleum refineries), 354 (misc. petroleum and coal products), and 390 (other manufacturing products).
The standard errors are in parentheses.
* indicates that the coefficient estimate is significant at the 10% level;
** indicates that the coefficient estimate is significant at the 5% level; and
*** indicates that the coefficient estimate is significant at the 1% level.
The log of human capital to labor ratio is from Hall and Jones (1999).

Table 7: Individual Country Regression: The United States

Dependent variable = $exporter_share_i$	
Coef. for $skill_i (\theta)$	0.587* (0.303)
Intercept (γ)	0.113 (0.092)
No. of observations	17
R^2	0.20

Notes: The observations are for 17 two-digit 1987 U.S. SIC industries excluding 21 (tobacco products), 29 (petroleum and coal products), and 39 (misc. manufacturing industries).
The standard errors are in parentheses.
* indicates that the coefficient estimate is significant at the 10% level;
** indicates that the coefficient estimate is significant at the 5% level; and
*** indicates that the coefficient estimate is significant at the 1% level.

Table 8: Comparison of Estimated Coefficients for Industry Skill Intensity among 4 Countries (with 17 two-digit U.S. SIC manufacturing industries)

Dependent variable = $exporter_share_i$	USA	Chile	Colombia	India
Coef. for $skill_i (\theta)$	0.587* (0.303)	0.534 (0.329)	0.248 (0.188)	-0.728 (0.579)
$\log(H/L)$	1.198	0.783	0.590	0.409

Notes: The coefficient for each country is estimated with 17 two-digit U.S. SIC industries excluding 21 (tobacco products), 29 (petroleum and coal products), and 39 (misc. manufacturing industries).
The standard errors are in parentheses.
* indicates that the coefficient estimate is significant at the 10% level;
** indicates that the coefficient estimate is significant at the 5% level; and
*** indicates that the coefficient estimate is significant at the 1% level.
The log of human capital to labor ratio is from Hall and Jones (1999).

Table 9: Concordance from three-digit ISIC (revision 2) to two-digit 1987 U.S. SIC

3-digit ISIC	Industry Description	2-digit usSIC	Industry Description
311	Food products	20	Food and kindred products
312	Animal feeds, etc		
313	Beverages		
(314)	(Tobacco products)	(21)	(Tobacco products)
321	Textiles	22	Textile mill products
322	Wearing apparel, except footwear	23	Apparel and other textile products
323	Leather products	31	Leather and leather products
324	Footwear, except rubber or plastic		
331	Wood products, except furniture	24	Lumber and wood products
332	Manufacture of furniture and fixtures, except primarily of metal	25	Furniture and fixtures
341	Paper and products	26	Paper and allied products
342	Printing and publishing	27	Printing and publishing
351	Industrial chemicals	28	Chemicals and allied products
352	Other chemicals		
(353)	(Petroleum refineries)	(29)	(Petroleum and coal products)
(354)	(Misc. petroleum and coal products)		
355	Rubber products	30	Rubber and misc. plastic products
356	Plastic products		
361	Manufacture of pottery, china and earthenware	32	Stone, clay, and glass products
362	Glass and products		
369	Other non-metallic mineral products		
371	Iron and steel	33	Primary metal industries
372	Non-ferrous metals		
381	Fabricated metal products	34	Fabricated metal products
382	Machinery, except electrical	35	Industrial machinery and equipment
383	Machinery electric	36	Electronic and other electric equipment
384	Transport equipment	37	Transportation equipment
385	Professional and scientific equipment	38	Instruments and related products
(390)	(Other manufactured products)	(39)	(Misc. manufacturing industries)

Note: Industries in parentheses are excluded for the estimation of the regression equations.

Source: Author's mapping.

Table 10: Cost Share of Skilled Labor ($skill_i$) in 17 two-digit U.S. SIC Manufacturing Industries

SIC	Industry	$skill_i$	SIC	Industry	$skill_i$
20	Food and kindred products	0.365	31	Leather and leather products	0.320
22	Textile mill products	0.246	32	Stone, clay, and glass products	0.311
23	Apparel and otr. textile products	0.297	33	Primary metal industries	0.291
24	Lumber and wood products	0.265	34	Fabricated metal products	0.369
25	Furniture and fixtures	0.337	35	Ind. machinery and equipment	0.490
26	Paper and allied products	0.314	36	Electronic and otr. elec. equip.	0.524
27	Printing and publishing	0.551	37	Transportation equipment	0.417
28	Chemicals and allied products	0.526	38	Instruments and related products	0.630
30	Rubber and misc. plastic prod.	0.352			

Notes: The cost share of skilled labor is measured as the non-production workers wages as the share in the annual payroll in each industry.

Manufacturing industries are classified according to the twp-digit 1987 U.S. SIC. The following categories are excluded: 21 (tobacco products), 29 (petroleum and coal products), and 39 (misc. manufacturing industries).

Source: 1992 U.S. Census of Manufactures.

Table 11: Regression for Four Countries and 17 two-digit U.S. SIC Manufacturing Industries

Dependent variable = $exporter\ share_{ic}$	
Coef. for $skill_i * \log(S/U)_c (\theta_2)$	0.762** (0.360)
No. of observations	68
R^2	0.64

Notes: The four countries are Chile, Colombia, India, and the United States. The following categories are excluded from the estimation: 21 (tobacco products), 29 (petroleum and coal products), and 39 (misc. manufacturing industries).

Country-specific dummies and industry-specific dummies are both included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table 12: Alternative Skilled-labor Cost Share in 17 two-digit U.S. SIC Manufacturing Industries: Wage Share of Workers with One or More Years of College Education

SIC	Industry	$skill_i$	SIC	Industry	$skill_i$
20	Food and kindred products	0.357	31	Leather and leather products	0.261
22	Textile mill products	0.259	32	Stone, clay, and glass products	0.371
23	Apparel and otr. textile products	0.213	33	Primary metal industries	0.379
24	Lumber and wood products	0.304	34	Fabricated metal products	0.383
25	Furniture and fixtures	0.281	35	Ind. machinery and equipment	0.452
26	Paper and allied products	0.426	36	Electronic and otr. elec. equip.	0.590
27	Printing and publishing	0.590	37	Transportation equipment	0.533
28	Chemicals and allied products	0.647	38	Instruments and related products	0.598
30	Rubber and misc. plastic prod.	0.383			

Note: See Appendix D for the details of calculation.

Source: Author's calculation from Morrow (2008).

Table 13. Alternative Relative Skilled-labor Abundance $(S/U)_c$ in Four Countries: Percentage of Population with Tertiary Education Attainment

	% Tertiary Education Attainment	Period of measurement	(Ref) Period for Exporter Fraction
Chile	8.9	Average of 1990 & 95	Average over 1990-96
Colombia	3.8	Average of 1980, 85, and 90	Average over 1981-91
India	3.2	Average of 1995 & 2000	Fiscal year 1997/98
United States	27.3	1990	1992

Notes: Educational attainment data for each country are selected for periods that correspond to the data periods of the exporter fractions.

Educational attainment data are available for every five years.

Source: Barro and Lee (2000).

Table 14: Regression for Four Countries and 17 two-digit U.S. SIC Manufacturing Industries with Alternative Measures of Industry Skill Intensity and Country Skill Abundance

Dependent variable = $exporter\ share_{ic}$	
Coef. for $skill_i * \log(S/U)_c (\theta_2)$	0.277** (0.113)
No. of observations	68
R^2	0.66

Notes: $skill_i$ is measured as the cost share of workers with one or more years of college education.

$(S/U)_c$ is measured as the percentage of population with any tertiary schooling.

Country-specific dummies and industry-specific dummies are both included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table 15: Relative Wage of Skilled to Unskilled Labor (s/w)

	(i) Max–Min Wage Ratio	(ii) Top10%– Bottom10% Mean Wage Ratio	(iii) Top 10 th –Bottom 10 th Percentile Wage Ratio	Data Periods
Chile	11.164	7.213	5.289	Average 1984-86
Colombia	9.694	5.670	3.379	Average 1988-90
India	30.280	13.218	5.662	Average 1997-98
United States	4.577	3.321	2.462	1992

Source: OWW Database (Oostendorp, 2005)

Table 16: Regression with Relative Factor Price (Skilled-to-Unskilled Wage Ratio):

Dependent variable = $exporter_share_{ic}$

Wage Ratio Measure	(i) Max–Min Wage Ratio	(ii) Top10%–Bottom10% Mean Wage Ratio	(iii) Top 10 th –Bottom 10 th Percentile Wage Ratio
Coef. for $skill_i * \log(s/w)_c$ (ψ)	-0.351 ** (0.166)	-0.492 ** (0.222)	-0.732 ** (0.302)
No. of observations R^2	68 0.64	68 0.65	68 0.65

Notes: Pooled data for the 17 two-digit U.S. SIC manufacturing industries for Chile, Colombia, India, and the United States are used for estimation.

$skill_i$ is measured as the non-production workers wages as the share in the annual payroll in each industry.

Country-specific dummies and industry-specific dummies are both included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table 17: Relative Wage of Skilled to Unskilled Labor (s/w), Measured Based on Same Occupations

	(i) Max–Min Wage Ratio	(ii) Top10%– Bottom10% Mean Wage Ratio	(iii) Top 10 th –Bottom 10 th Percentile Wage Ratio	Data Periods
Chile	7.434	5.555	4.894	Average 1985-86
Colombia	4.665	3.494	3.001	1988
India	8.987	6.824	5.795	Average 1997-98
United States	2.974	2.560	2.359	1992

Notes: The relative wage is measured based on the set of the following 25 occupations in the ILO October Inquiry codes: 30, 36, 59, 65, 67, 70, 82, 84, 85, 88, 90, 91, 95, 96, 97, 99, 100, 129, 130, 131, 133, 134, 135, 140, and 141.

Source: OWW Database (Oostendorp, 2005)

Table 18: Regression with Relative Factor Price (Skilled-to-Unskilled Wage Ratio) Measured Based on Same Occupations:

Dependent variable = $exporter\ share_{ic}$

Wage Ratio Measure	(i) Max–Min Wage Ratio	(ii) Top10%–Bottom10% Mean Wage Ratio	(iii) Top 10 th –Bottom 10 th Percentile Wage Ratio
Coef. for $skill_i * \log(s/w)_c (\psi)$	-0.587** (0.243)	-0.645** (0.273)	-0.674** (0.288)
No. of observations	68	68	68
R ²	0.65	0.65	0.65

Notes: Pooled data for the 17 two-digit U.S. SIC manufacturing industries for Chile, Colombia, India, and the United States are used for estimation.

$skill_i$ is measured as the non-production workers wages as the share in the annual payroll in each industry.

Country-specific dummies and industry-specific dummies are both included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C1: Country-Industry-Year Pooled Regression (1): without Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.390*** (0.105)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	0.977*** (0.165)
No. of observations	340
R ²	0.25

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C2: Country-Industry-Year Pooled Regression (2): with Industry Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.758*** (0.124)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	0.993*** (0.116)
No. of observations	340
R ²	0.61

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Industry-specific dummies are included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C3: Country-Industry-Year Pooled Regression (3): with Country Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.252 (0.400)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	0.819 (0.593)
No. of observations	340
R ²	0.31

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Country-specific dummies are included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C4: Country-Industry-Year Pooled Regression (4): with Year Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.137 (0.193)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	0.649** (0.300)
No. of observations	340
R ²	0.34

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Year-specific dummies are included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C5: Country-Industry-Year Pooled Regression (5): with Industry and Country Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.663** (0.315)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	0.968** (0.411)
No. of observations	340
R ²	0.66

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Industry- and Country-specific dummies are both included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C6: Country-Industry-Year Pooled Regression (6): with Industry and Year Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.568*** (0.144)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	0.650*** (0.192)
No. of observations	340
R ²	0.70

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Industry- and Year-specific dummies are both included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C7: Country-Industry-Year Pooled Regression (7): with Country and Year Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.309 (0.418)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	0.896 (0.622)
No. of observations	340
R ²	0.34

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Country- and Year-specific dummies are both included.

Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Table C8: Country-Industry-Year Pooled Regression (8): with Industry, Country, and Year Dummies

Dependent variable = <i>exporter share_{ict}</i>	
Coef. for <i>skill_{ict}</i> (θ_1)	-0.975*** (0.345)
Coef. for <i>skill_{ict}</i> *log(<i>S/U</i>) _c (θ_2)	1.140*** (0.442)
No. of observations	340
R ²	0.70

Notes: Data are for 17 manufacturing industries according to the two-digit 1987 U.S. SIC for the following countries and years: Chile (1990-96), Colombia (1981-1991), India (1998), and the U.S. (1992).

Industry-, Country- and Year-specific dummies are all included.

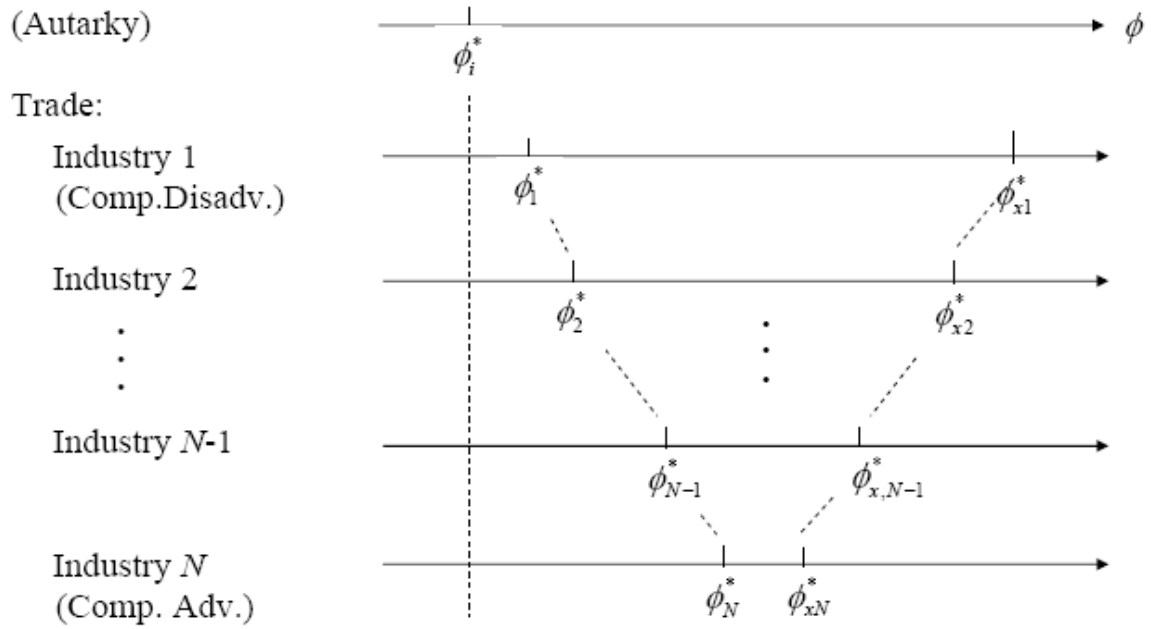
Robust standard errors are shown in parentheses.

* indicates that the coefficient estimate is significant at the 10% level;

** indicates that the coefficient estimate is significant at the 5% level; and

*** indicates that the coefficient estimate is significant at the 1% level.

Figure 1: “Gap” between Productivity Cutoffs in Costly-Trade Equilibrium
(for Skilled-labor Abundant Country)



Note: The rank of industry skill intensities (the Cobb-Douglas production cost shares) are as follows: $\beta_1 < \beta_2 < \dots < \beta_N$.

Figure 2: Fraction of Exporters among All Active Firms vs Industry Skill Intensity: Chile

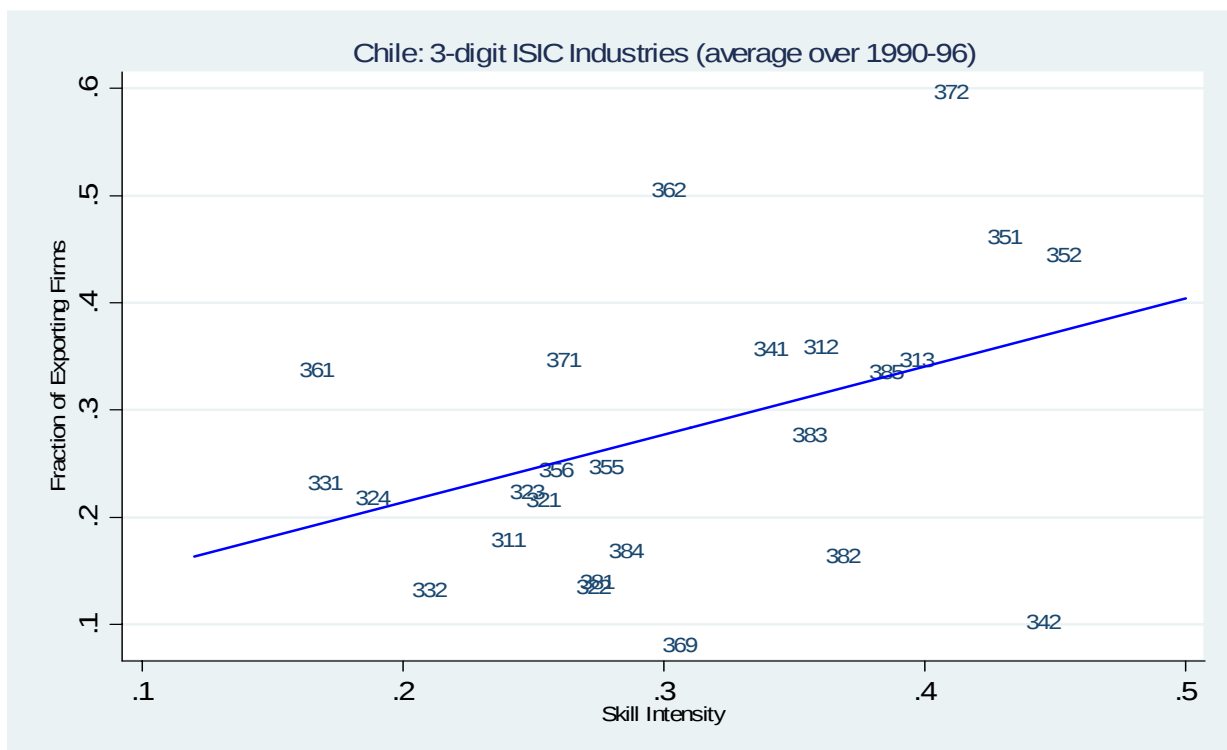


Figure 3: Fraction of Exporters among All Active Firms vs Industry Skill Intensity: Colombia

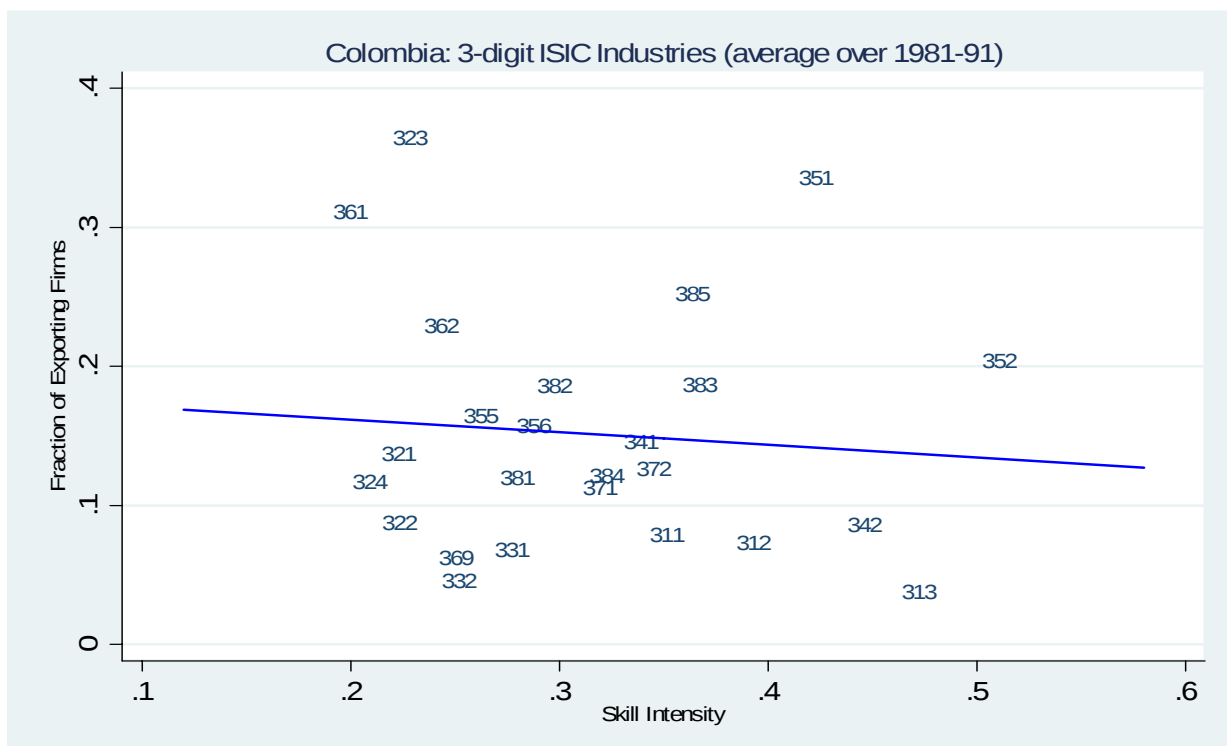


Figure 4: Fraction of Exporters among All Active Firms vs Industry Skill Intensity: India

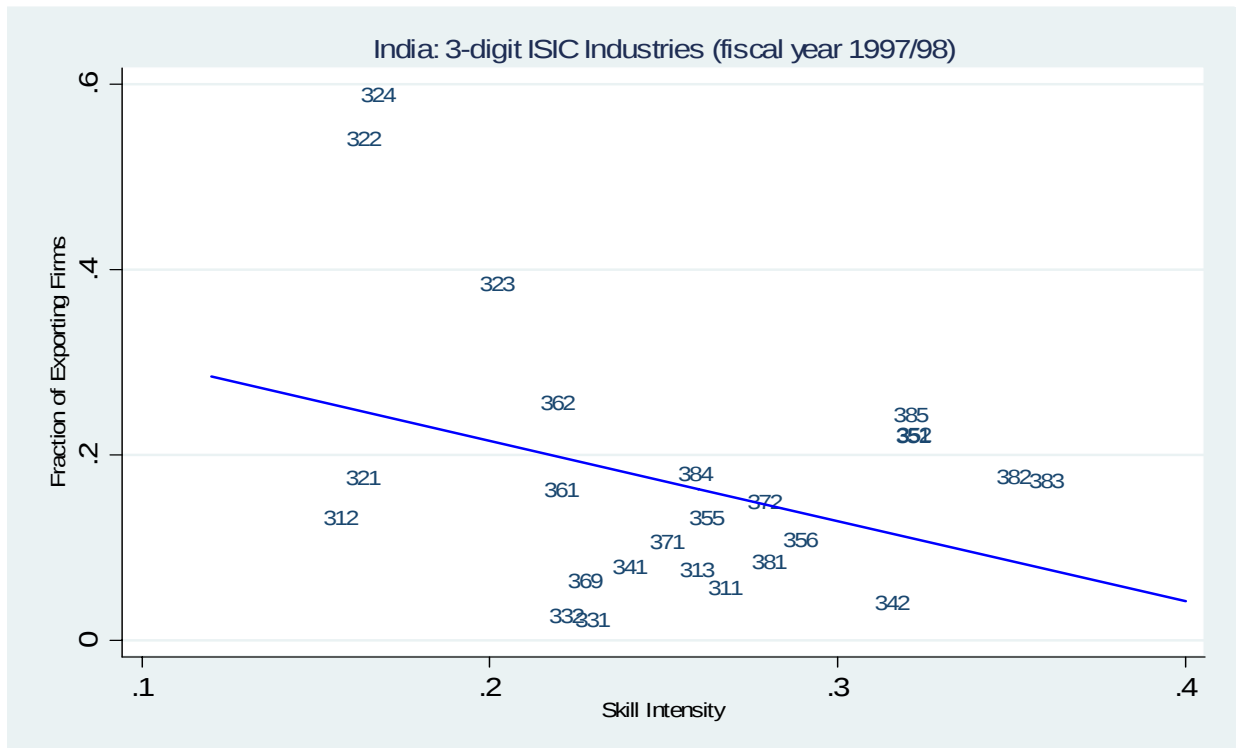


Figure 5: Fraction of Exporters among All Active Firms vs Industry Skill Intensity:
the United States

