

# Do Importing and Exporting Increase the Demand for Skilled Workers? Plant-level Evidence from Indonesia

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## Abstract

This paper estimates the impact of plant-level import and export decisions on the demand for skilled labor. We allow for import and export effects to vary across plants and for plants to self-select into importing and exporting with some knowledge of their gains from such actions. Using an Indonesian manufacturing data set that contains the detailed plant-level information on workers' education levels, we apply the treatment effect framework developed by Heckman and Vytlacil (1999, 2005, 2007a,b) to identify the average effect of importing and exporting on skill demand across different sub-groups of plants, such as importers, non-importers, exporters, and non-exporters. We find that the effect of importing on skill demand among importers is substantially larger than among non-importers, providing evidence that the effect of importing on skill demand is heterogeneous and that plants self-select into importing based on the gains from importing. The results also indicate a large positive effect of importing on skill demand both within production workers and within non-production workers. On the other hand, exporting leads to skill upgrading within non-production workers but it does not necessarily increase the skill demand for production workers.

## 1 Introduction

Understanding the effect of trade on income inequality has been emphasized as a key issue in developing countries (Goldberg and Pavcnik, 2006). Numerous studies provide empirical evidence that trade liberalization may have contributed to an increase in the skill premium

across several developing countries (Hanson and Harrison (1999), Gindling and Robbins (2001), Attanasio et al. (2004)). While empirical evidence suggests that the skill premium increase in developing countries was driven by an increase in the demand for skilled workers (Sanchez-Paramo and Schady, 2003; Goldberg and Pavcnik, 2007), the underlying cause of the increased demand for skilled workers is still an unresolved, but equally important, issue.

The rise in skill premium after trade liberalization in developing countries is inconsistent with the predictions of Heckscher-Ohlin (H-O) theory. Specifically, lower trade barriers are predicted to lead to a decrease in skill premiums by decreasing the demand for skilled labor through a shift of resources from skill-intensive industries to skill-scarce industries in skill-scarce developing countries. In contrast, empirical evidence indicates that the reallocation of non-production and production workers across industries explains little of the changes in the demand for skilled workers; most of the increase in the demand for skilled labor happens within firms rather than across firms/industries (Berman, Bound, and Griliches, 1994; Bernard and Jensen, 1997; and Biscourp and Kramarz, 2006). Thus, to understand the effect of trade on skill premium, it is important to understand how the demand for skilled labor at the firm-level is affected by trade.

This paper empirically examines how the demand for skilled workers is related to plant-level import and export decisions using the exceptionally detailed plant-level panel data covering all the plants employing more than 20 workers in the Indonesian manufacturing sector. Using foreign intermediate goods in production often requires the adoption of more sophisticated technology, particularly when it is imported from industrialized nations for which there is substantial evidence of skill-biased technological change.<sup>1</sup> Similarly, exporting may provide an opportunity to get better access to skill-biased foreign technology (Clerides et al., 1998). Skill-biased technological change may also have a significant effect on the skill premium in developing countries (e.g., Kijima, 2006), and importing and exporting at plant-level may induce the adoption of skill-biased technology.

The impact of trade on the demand for skill within firms may vary substantially across heterogeneous firms. For instance, importing foreign intermediate goods may provide firms with an incentive to hire more skilled workers, but the degree of skill-upgrading may depend crucially on the firm's existing (potentially unobserved) heterogeneous ability to implement foreign technology. When the effect of importing on skill demand varies across firms, there is no single "effect" of importing on skill demand. Further, we expect firms with greater ability to adopt technology will self-select into importing, leading to a difficult selection problem. In such a case, the instrumental variable (IV) estimator does not identify the average impact of importing. Imbens and Angrist (1994) show that, under some conditions, instrumental variables

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<sup>1</sup>Doms, Dunne, and Troske (1997) provide evidence that the adoption of new factory automation technologies lead to skill upgrading. Further, recent literature on trade and heterogeneous firms suggests that importing foreign intermediate goods increases productivity. Muendler (2004), Halpern, Koren, and Szeidl (2006), Kasahara and Rodrigue (2008), Amiti and Konings (2008), Kugler and Verhoogen (2009). Adoption of skilled-biased technology may be the reason why importing intermediates increases productivity.

identify the average effect of importing among firms induced to change their import status by the instrument.

In this study, allowing for a possibility that the impact of trade on skill demand is heterogeneous across firms, we employ the treatment effect framework developed by Heckman and Vytlacil (1999, 2005, 2007a,b) to estimate the average effect among all firms, the average effect among importers (or exporters), and the average effect among non-importers (or non-exporters); they are called the Average Treatment Effect (ATE), the Treatment Effect on the Treated (TT), and the Treatment Effect on the Untreated (TUT), respectively.

The data set contains plant-level information on the education level of workers (e.g., junior high-school, high-school, bachelor, Ph.D, etc.) across production and non-production occupational categories for the years of 1996 and 1997. We examine the effect of importing and exporting on the relative demand for skills measured by the logarithm of the ratio of the number of workers with at least a high school degree and that with less than a high school degree. To control for the endogeneity of importing and exporting decisions, we utilize the variations in input and output tariffs at 5-digit industry level and their interaction terms with plant labor productivity.

Using the skill measure based on worker's education level is the major advantage over the existing empirical literature studying the effect of international trade on the demand for skills which uses occupation categories, such as non-production or white-collar, to construct a proxy for skilled labor (Bernard and Jensen, 1999; Harrison and Hanson, 1999; Pavcnik, 2003; Biscourp and Kramarz, 2006). The exception is Bustos (2007). Bustos examines the impact of exporting on skill upgrading using a panel of Argentinean manufacturing firms with the detailed information on worker's education level and finds that exporting increases the demand for skills, while our results suggest that importing is more important for skill upgrading than exporting.

Our analysis provides evidence for the heterogeneous effect of importing on skill demand across firms. We find that the average effect of importing on skill demand among firms who self-select into importing (TT) is substantially larger than the average effect among those who choose not to import (TUT), indicating that the impact of importing on skill demand is positive even among firms who does not import. On the other hand, the effect of exporting on skill demand is less clear.

We also examine the impact of importing and exporting on skill-upgrading within occupational classes of workers. We find a large positive effect of importing on skill demand, especially for importers, both within production workers and within non-production workers. Thus, missing the skill upgrading within each of occupation categories, the conventional skill measure based on the ratio of non-production workers and production workers in the previous studies may underestimate the impact of importing on skill demand. Our estimates also indicate that the impact of exporting on skill demand within non-production workers is significantly positive, but we find no evidence for the impact of exporting on skill demand within production workers.

The next section describes our data set. Our empirical framework is discussed in Section 3. Section 4 provides the results, and the last section concludes.

## 2 Data and Descriptive Statistics

Our data set is based on the Indonesian manufacturing census between 1991 and 1997 which covers all plants with at least 20 employees. For this study, we mainly use the data for the years of 1996 and 1997 since these two years contain detailed information on workers' education levels. This data provides numerous advantages in this context.

First, the data set contains plant-level information on the education level of workers for each of production and non-production (or white-collar and blue-collar) occupational categories for the years of 1996 and 1997, which allows us to construct the relative skill measures based on workers' education levels. This is a major advantage over the existing empirical literature studying the effect of international trade on the demand for skilled labor which often uses occupation categories, such as non-production or white-collar, to construct a proxy for skilled labor (Bernard and Jensen, 1999; Harrison and Hanson, 1999; Pavcnik, 2003; Biscourp and Kramarz, 2006).

Second, the data set includes information on export sales and the cost of imported intermediates to identify the effect of exporting and importing on the demand for skilled labor. Additional plant-level information contained in the data includes the percentage of foreign ownership, total expenses on research and development (R&D), and total expenses on training. If R&D activities are necessary for the adoption of foreign skill-based technology, investigating how R&D expenditures are affected by export and import decisions provides important information about the effect of international trade on the demand for skills. Total expenses on training can be interpreted as the measure of human capital investment within a firm. On the one hand, a firm may try to meet the increased demand for skills by training the existing workforce in addition to hiring better educated workers; on the other hand, training workers may improve firm's ability to adopt foreign technology.

Finally, as mentioned in Amiti and Konings (2008) and Amiti and Davis (2008), Indonesia experienced trade liberalization during the period covered by this data set and the data on input and output tariffs are available at 5 digit ISIC industry-level.<sup>2</sup> Both types of tariffs vary substantially across years and industries. We utilize the variations in input and output tariffs to control for the endogeneity of importing and exporting decisions when we estimate the effect of importing and exporting on the demand for skilled workers. Then, we use the estimated results to quantify how much changes in input/output tariffs affect the demand for skilled workers through their effects on the adoption of skill biased technology.

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<sup>2</sup>Given the detailed information on individual inputs at plant level, input tariffs can be constructed at 5 digit ISIC industry-level. See Amiti and Konings (2008).

Table 1 presents the descriptive statistics on the relationship between various skill measures and four different export/import status for 1996-1997 for domestic and foreign plants. As reported in the last columns, the sample size is large at 38393 even we restrict our sample to 1996 and 1997. We classify a plant as foreign plant when at least 10 percent of its equity is held by foreign investors. Since there are few examples of data describing how workers' education levels differ across export/import status in the existing studies, we provide the detailed descriptive statistics for the education-based skill measures, including a fraction of workers with six different education categories classified by the highest degree completed: no primary education, primary education, junior high school, high school, college, and graduate school.

In Table 1, importers and exporters tend to employ more educated workers than domestically-oriented plants. For instance, on average, a fraction of college graduates in total workers is 6.3 percent for plants that both export and import while the corresponding figure for plants that neither export nor import are only 1.8 percent. Similarly, a fraction of workers beyond high-school degree for plants that both export and import is 56.5 percent but, for domestic non-exporters and non-importers, it is only 22.6 percent. The workers of foreign plants are generally more educated than those of domestically owned plants.

Conditional on import status, the worker's education level of non-exporting plants appears to be higher than that of exporting plants. This pattern is especially apparent for foreign plants. This is possibly because foreign firms are conducting vertical foreign direct investment by setting up a production facility that is specialized in unskilled-labor intensive production processes in Indonesia. As opposed to foreign plants, the average education level of exporting domestic plants is higher than that of non-exporting plants although importing domestic plants employ more educated workers than exporting domestic plants. On the other hand, conditional on export status, importers hire more educated workers than non-importers; for instance, the workers of plants that import but do not export, denoted by "No-Ex/Im," are more educated than those of plants that both exports and imports.

The last three columns report alternative skill related variables. "Training/Worker" and "R&D/Worker" report the average per worker expenditures on training and R&D, respectively, in the unit of 1983 hundred thousands Indonesia rupiah while "Non-Prod./All Workers" reports a fraction of non-production workers in all workers. Importers and exporters engage in more training and R& D activities, and employ more non-production workers than plants that neither export nor import. The per worker expenditures on training and R&D activities of importers are higher than those of exporters. Foreign plants, especially those who import intermediate goods from abroad, tend to spend more resources on training and R&D activities and hire more non-production workers than domestically owned plants.

Table 2 reports the descriptive statics for each of production and non-production occupation categories. Non-production workers are much more educated than production workers across export/import status and domestic/foreign ownership. For instance, on average across all plants,

a fraction of college graduates for non-production workers is 13.1 percent while a fraction of college graduates for production workers is substantially smaller at 1.1 percent.

The education levels of workers are different across import and export status even within production and non-production occupation categories. On average, a fraction of college graduates for production workers is 3.0 percent at plants that both import and export while less than 1 percent of production workers have college degrees at domestically oriented plants. Similarly, 25.0 percent of non-production workers are college graduates at importing and exporting plants while a fraction of college graduates among non-production workers is only 9.8 percent at non-importing and non-exporting plants. Given the observed large differences in skill demands across import and export status within occupation categories, this paper examine the effect of importing and exporting on the demand for skills separately for production workers and non-production workers.

The last column of Table 2 reports a fraction of plants that do not hire any non-production worker. Overall, 20.6 percent of plants do not hire any non-production worker. Plants that import and export are more likely to hire at least one non-production worker while domestically oriented plants that neither export nor import is most likely to hire no one in non-production occupation category. Foreign plants are more likely to hire non-production workers than domestic plants. Thus, whether plants hire at least one non-production workers or not is related to import and export status as well as foreign ownership.

### 3 Empirical Framework

This section develops our empirical framework to analyze the impact of importing and exporting on skill demand. For brevity, our discussion mainly focuses on importing but it is also possible to incorporate exporting into the model as in Kasahara and Lapham (2008).

#### 3.1 Model with Heterogeneous Adoption of Skill-Biased Technology

Consider a constant elasticity of substitution (CES) production function as follows:

$$f(L_s, L_u, A, \varphi) = \varphi \left\{ [AL_s]^{(\sigma-1)/\sigma} + L_u^{(\sigma-1)/\sigma} \right\}^{\sigma/(\sigma-1)}, \quad (1)$$

where  $L_s$  is the skilled labor input,  $L_u$  is the unskilled labor input,  $\sigma > 1$  is elasticity of substitution between skilled and unskilled labor,  $\varphi$  is Hicks neutral technology term, and  $A$  is skilled labor augmenting technology term.

Denote the log of demand for skilled labor input relative to unskilled labor input by  $S \equiv \ln(L_s/L_u)$ . Given the market wages, the relative demand for skilled labor input is determined by equating the ratio of the marginal product of skilled and unskilled labor to the ratio of their

wages as

$$S = (\sigma - 1) \ln A - \sigma \ln (w_s/w_u), \quad (2)$$

where  $w_s$  and  $w_u$  are the wages for skilled and unskilled labor inputs, respectively.

To test whether importing increases the relative demand for skilled labor input, we consider a possibility that importing foreign inputs affects the level of skilled labor augmenting technology as

$$(\sigma - 1) \ln A(X, D) = D\beta + X\gamma' + U, \quad (3)$$

where  $\beta$  is a parameter that captures the effect of importing on skill-biased technology level;  $X$  is a vector of observables;  $U$  is skill-biased technology shock. Then, the skill demand is given by

$$S = D\beta + X\gamma' + U, \quad (4)$$

where, with some abuse of notation, the second term on the right hand side of (2),  $-\sigma \ln (w_s/w_u)$ , is incorporated into one of the variables in  $X$ , for instance, as industry/time dummies.

It is plausible to think that import decision  $D$  and skill-biased technology shock  $U$  are correlated. A firm with more advanced skill-biased technology (i.e., high value of  $U$ ) may self-select into importing ( $D = 1$ ) because the gain from importing is increasing in the value of  $U$ . In such a case, the ordinary least squares estimator (OLS) of  $\beta$  is subject to this “standard” endogeneity bias. If an instrument that is correlated with  $D$  but uncorrelated with  $U$  is available, the method of instrumental variable (IV) identifies  $\beta$  when  $\beta$  is a constant parameter.

The standard model assumes that the effect of  $D$  on  $S$  is the same across firms. This is a strong assumption. What if the effect of importing on skilled demand is heterogeneous across plants so that  $\beta$  is different across plants? In such a case, there is no single parameter  $\beta$  to estimate and, further, plants may sort into importing on the basis of their knowledge of  $\beta$ .

For instance, importing may provide better opportunities for a firm to adopt foreign skill-biased technology. If we interpret the value of  $\beta$  as the ability for a firm to adopt the skill-biased technology upon importing, the impact of importing on the demand for skilled workers would be heterogeneous whenever the firms’ ability to adopt foreign technology is heterogeneous.<sup>3</sup> When a firm knows its ability to adopt skill-biased technology, a firm with greater ability to adopt skilled-biased technology will self-select into importing because it can successfully adopt foreign technology upon importing. Because of this positive sorting on the gain from importing, the value of  $\beta$  tends to be higher for a plant that chooses to import than for a plant that chooses not to import.

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<sup>3</sup>The adoption of skill-biased technology is specified in reduced-form through equation (3). In principle, we may extend the model further by explicitly considering a decision to adopt foreign technology, and this is important direction for future research.

We extend the model in (4) by assuming that  $\beta$  is a variable coefficient with

$$\beta = \bar{\beta} + \epsilon, \tag{5}$$

where  $\bar{\beta}$  is the mean of  $\beta$  while  $\epsilon$  is unobservable to a researcher but is, at least partially, known to the firm’s manager. Then (4) is written as

$$S = [\bar{\beta} + \epsilon]D + X\gamma' + U. \tag{6}$$

In this “random-coefficient” setup, the effect of importing on skill-demand is heterogeneous. Imbens and Angrist (1994) show that, under some conditions, an instrumental variable estimator identifies the average value of  $\beta$  for firms induced change their import choice by the instrument. Since not all firms will be induced to switch their import status by an instrument, the average value of  $\beta$  across all firms,  $\bar{\beta}$ , is not identified by the instrumental variable (IV) estimator.

As Card (2001), Heckman, Urzua, and Vytlacil (2006), and Heckman and Vytlacil (1999, 2005, 2007a,b) further argue that, in this random coefficient case, different instrumental variables (IV) lead to different IV estimates of the impact of importing on skill demand. To see this, let  $Z$  is a vector that contains  $X$  and an instrument that is correlated with the import decision  $D$  but is uncorrelated with the error term  $U$  in (4) so that  $Cov(Z, D) > 0$  and  $Cov(Z, U) = 0$ . Then, conditional on  $X$ , as the sample size goes to infinity, the instrumental variable estimator approaches the probability limit of

$$\frac{Cov(Z, S)}{Cov(Z, D)} = \bar{\beta} + \frac{Cov(Z, \epsilon D)}{Cov(Z, D)}.$$

In general,  $Cov(Z, \epsilon D) \neq 0$  since  $D$  and  $\epsilon$  are correlated when firms self-select into importing based on their knowledge of  $\epsilon$ . Then, the instrumental variable estimator does not identify the average impact  $\bar{\beta}$ . Furthermore, different instruments lead to different “bias terms” because in general  $Cov(Z, \epsilon D)/Cov(Z, D) \neq Cov(Z', \epsilon D)/Cov(Z', D)$  for two different instruments  $Z$  and  $Z'$ . Two distinct empirical studies on the impact of importing and exporting on skill demand could produce different conclusions when they use different instrumental variables.

Since the treatment effect of importing on skill demand is heterogeneous, we will construct and report different “summary statistics” for the treatment effect.<sup>4</sup> In particular, we consider the average effect of importing on skill-demand among importers (the treatment effect on the treated, TT), the average effect among non-importers (the treatment effect on the untreated, TUT), and the average effect among all firms (the average treatment effect, ATE). If a firm with high value of  $\epsilon$  self-selects into importing, the average value of  $\beta$  among importers (TT) would be higher than the average value of  $\beta$  among non-importers (TUT).

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<sup>4</sup>While the main object of interest is the (conditional) distribution of  $\beta$ , identifying the distribution of  $\beta$  is a difficult task. In this paper, we attempt to construct some summary measure of the population distribution of  $\beta$ .

### 3.2 The Import Decision

To clarify the nature of self-selection into importing, we provide a simple static model of firm's import decision in which a firm's ability to adopt skill-biased technology is heterogeneous.

The marginal cost of producing one unit of output is given by  $c(A, \varphi) = \min_{\{L_s, L_u\}} w_s L_s + w_u L_u$  subject to  $f(L_s, L_u, A, \varphi) \geq 1$ . As specified in (3) and (5), importing may increase the skill-biased technology level  $A$  and, further, such an effect of importing is heterogeneous across firms. For simplicity, we assume that importing does not affect the Hicks neutral technology level  $\varphi$ .<sup>5</sup>

Let  $Z$  denote a vector of observed variables containing  $X$  and other observables that serve as instruments. The firm faces demand function  $q = B(Z)p^{-\eta}$ , where  $q$  is quantity demanded,  $p$  is output price, and  $B(Z)$  is demand shifter. Denote gross profit by  $r(A, \varphi, Z) = \max_q pq - c(A, \varphi)q$ . When a firm chooses to import, it incurs an importing cost  $f_m(Z)$ . Then firm's net profit function is  $\pi(A, \varphi, Z, D) = r(A, \varphi, Z) - Df_m(Z)$ .

A firm imports if  $\pi(A(X, 1), \varphi, Z, 1) - \pi(A(X, 0), \varphi, Z, 0) \geq 0$ . Define a latent variable

$$D^* = \pi(A(X, 1), \varphi, Z, 1) - \pi(A(X, 0), \varphi, Z, 0) = \mu_D(Z) - V,$$

where  $\mu_D(Z) = E[\pi(A(X, 1), \varphi, Z, 1) - \pi(A(X, 0), \varphi, Z, 0)|Z]$  is a deterministic function of observable variables  $Z$  while  $V = [\pi(A(X, 1), \varphi, Z, 1) - \pi(A(X, 0), \varphi, Z, 0)] - \mu_D(Z)$  is a mean-zero unobserved stochastic component. This leads to a latent variable model as

$$\begin{aligned} D^* &= \mu_D(Z) - V, \\ D &= 1 \quad \text{if } D^* \geq 0, \quad D = 0 \quad \text{otherwise.} \end{aligned} \tag{7}$$

A firm imports, i.e.,  $D = 1$ , if  $D^* \geq 0$ ; it does not import otherwise.

The random variable  $V$  captures both idiosyncratic productivity shock  $\varphi$  and the random components in the skill-biased technology level,  $\epsilon$  and  $U$ . Since  $\pi(A(X, 1), \varphi, Z, 1) - \pi(A(X, 0), \varphi, Z, 0)$  is strictly increasing in the value of  $\epsilon$ , the random variables  $V$  and  $\epsilon$  are negatively correlated when  $\epsilon$  is independent of  $\varphi$  and  $U$ . This implies that a firm with high value of  $\epsilon$ —high ability of adopting foreign technology—is more likely to self-select into importing. That is, a firm with high ability of adopting the skill-biased technology is more likely to import because its gain from adopting more advanced skill-biased technology induced by importing is larger.

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<sup>5</sup>This is an extreme assumption but the similar argument goes through when the impact of importing on the skill-biased technology  $A$  is sufficiently large relative to its impact on the Hicks neutral technology level  $\varphi$ .

### 3.3 The Marginal Treatment Effect

To evaluate the heterogeneous impact of importing on skill demand, we use the framework developed by Heckman and Vytlacil (1999, 2005, 2007a,b). Let  $S_1$  be the log of potential demand for skilled labor relative to unskilled labor input as an importer, and  $S_0$  be the log of potential relative skill demand as a non-importer. We can write the relative demand for skilled labor input, depending on import status, as

$$S_1 = \mu_1(X) + U_1 \text{ and } S_0 = \mu_0(X) + U_0, \quad (8)$$

where, allowing for the average value of  $\beta$  to depend on  $X$  in (6),  $\mu_1(X) \equiv E[S_1|X] = \bar{\beta}(X) + X\gamma'$  and  $\mu_0(X) \equiv E[S_0|X] = X\gamma'$  while  $U_1 = \epsilon + U$  and  $U_0 = U$ . The impact of importing on the skill demand depends on the ability of adopting skill-biased technology as

$$S_1 - S_0 = \bar{\beta}(X) + U_1 - U_0.$$

For a firm's decision to import, we consider a latent variable model (7). In (7), we assume that  $Z$  is the vector of observed variables that are assumed to be independent of  $(U_0, U_1, V)$ . The set of variables in  $X$  can be a subset of  $Z$  but, for identification, we assume that  $Z$  contains at least one "instrument" that is not in  $X$ .

The distribution of  $V$ , denoted by  $F_V$ , is assumed to be continuous and strictly increasing. Further, we allow  $V$  to be dependent on  $U_1$  and  $U_0$ ; as discussed in the previous section, we expect that a firm with a larger value of  $U_1 - U_0 = \epsilon$  has a larger gain from importing due to higher ability of adopting technology, and hence the value of  $V$  is low. This means that  $E[U_1 - U_0|V]$  is decreasing in  $V$ .

Denote the probability of importing conditional on  $Z$  by  $P(Z)$  so that  $P(Z) = \text{Prob}(\mu_D(Z) > V) = F_V(\mu_D(Z))$ . Define a uniform random variable  $U_D \equiv F_V(V)$  and then the importing decision (7) is alternatively written as  $D = 1$  if  $P(Z) \geq U_D$  and  $D = 0$  otherwise. Note that if  $E[U_1 - U_0|V]$  is strictly decreasing in  $V$ , so is  $E[U_1 - U_0|U_D]$  in  $U_D$ . Define the marginal treatment effect (MTE) as

$$\Delta^{MTE}(x, p) = E[S_1 - S_0|X = x, U_D = p] = E[\mu_1(X) - \mu_0(X) + U_1 - U_0|X = x, U_D = p]. \quad (9)$$

This is the mean treatment effect for firms with  $X = x$  and  $P(Z) = p$  when  $U_D = p$ . That is, it is the mean impact from importing on skill demand for firms with  $X = x$  and  $P(Z) = p$  when the realization of unobserved random variable  $U_D$  is such that firms are indifferent between importing and not importing. The MTE helps us to identify the heterogeneity in the impact of importing on skill demand across firms. Furthermore, as Heckman and Vytlacil (2005, 2007a, 2007b) establish, we can express all the conventional treatment parameters (ATE, TT, TUT,

IV, and OLS) as weighted averages of MTE with different weighting function. In particular, different instrumental variables weight MTE differently. The appendix discusses how to estimate various treatment parameters in detail.

### 3.4 Skill measure

We classify between skilled labor and unskilled labor based on the worker’s education level. In the large empirical literature in labor economics on skill premium and skill biased technological change (Berman, Bound, and Griliches, 1994; Autor, Katz, and Krueger, 1998; and Card and DiNardo, 2002), the number of college graduates and the number of high school graduates are often used as the measures of skilled labor and unskilled labor, respectively. Since the average education level in Indonesia is low as indicated in Table 1, we define workers with at least high-school degree as skilled labor while those with less than high-school degree as unskilled labor.

Specifically, we construct skilled labor  $L_s$  by converting workers with some college education, bachelor, master, and doctor degrees to high-school graduate equivalent using an 8.7 percent rate of return to education as  $L_s = \text{high-school+} + \text{some-college} \times \exp(2r) + \text{bachelor} \times \exp(4r) + \text{master} \times \exp(6r) + \text{doctor} \times \exp(9r)$  with  $r = 0.087$ .<sup>6</sup> Similarly, the measure of unskilled labor  $L_u$  is constructed by converting workers with primary education and junior-high-school degree to workers without any primary education (no-primary) as  $L_u = \text{no-primary} + \text{primary} \times \exp(6r) + \text{junior-high-school} \times \exp(9r)$ . The 8.7 percent rate of return to education is from Duflo (2001) who estimates the wage regression in Indonesia using regional variation in the number schools across cohorts induced by the timing of the school construction programs.

### 3.5 Instruments

We construct a set of instruments based on input and output tariffs at 5 digit ISIC industry-level obtained from Amiti and Konings (2008). As Amiti and Konings (2008) show, both types of tariffs vary substantially across industries and years between 1991-1997.

To capture the non-linear effect of tariff rates, we first construct dummy variables based on 10, 50, and 90 percentile of the distribution of tariff rate in 1996 and 1997.<sup>7</sup> Specifically, for input tariff, we define  $D_{\tau_m,1} = 1(0.085 \leq \tau_m < 0.156)$ ,  $D_{\tau_m,2} = 1(0.037 \leq \tau_m < 0.085)$ , and  $D_{\tau_m,3} = 1(\tau_m < 0.037)$ , where  $\tau_m$  is input tariff rate of 5-digit ISIC industry each plant belongs to. The baseline tariff rate dummy excluded from a regression is a dummy of the highest range

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<sup>6</sup>When we examine skill demand equation within production workers, we use  $L_s = \text{junior-high-school} + \text{high-school} \times \exp(3r) + \text{some-college} \times \exp(5r) + \text{bachelor} \times \exp(7r) + \text{master} \times \exp(9r) + \text{doctor} \times \exp(12r)$ .

<sup>7</sup>Estimating the decision of Canadian plants to start exporting to the United States by the probit, Lileeva and Trefler (2009) find that continuous variable of tariff cut in the U.S. is not statistically significant while a binary variable constructed from the threshold tariff-cut value is significant with expected sign. They argue that this is because of the nonlinear effect of tariff cut.

of tariff rates,  $D_{\tau_m,0} = 1(0.156 \leq \tau_m)$ , so that the coefficients on  $D_{\tau_m,1}$ ,  $D_{\tau_m,2}$ , and  $D_{\tau_m,3}$  in import decision regression captures the effect of reducing tariff rates on importing.

Further, as suggested in the model of Melitz (2003) and Kasahara and Lapham (2008), the effect of tariff rates on importing and exporting may crucially depend on plant productivity level; a plant with very low productivity may not respond even to a large reduction of tariff rate while a plant with high productivity may start importing with a small reduction of tariff rate. To capture such an effect, we also consider the interaction terms between plant labor productivity and tariff dummies as additional instruments. In sum, we use  $D_{\tau_m,1}$ ,  $D_{\tau_m,2}$ ,  $D_{\tau_m,3}$ , and their interaction terms with plant labor productivity are included in import decision equation but excluded from skill demand equation (4) and will serve as our instrument for importing.

A set of instruments for exporting is similarly constructed as  $D_{\tau_x,1} = 1(0.150 \leq \tau_x < 0.238)$ ,  $D_{\tau_x,2} = 1(0.048 \leq \tau_x < 0.150)$ ,  $D_{\tau_x,3} = 1(\tau_x < 0.048)$ , and their interaction terms with plant labor productivity, where  $\tau_x$  denotes output tariff rate of 5-digit ISIC industry each plant belongs to.

## 4 Results

### 4.1 Decision to Import and Export

To examine the validity of our instruments for importing and exporting, Table 3 reports the results from the logit of the probability of importing or exporting with different set of regressors. The set of plant-level controls are as follows: “Labor Prod” is the logarithm of labor productivity; “Foreign” indicates a dummy for foreign ownership; “R&D” takes a value of one when R&D expenditure is strictly positive, and zero otherwise; “Training” is also a dummy for training that takes a value of one when training expenditure is positive; and “Capital/Worker” is the logarithm of capital per worker. All regressions include 3 digit industry effects and year effects.

Column (1) of Table 3 includes both input tariff rate and its interaction term with labor productivity with labor productivity and foreign ownership as additional controls. As expected, the sign on the interaction term is negative and significant, suggesting that a reduction of input tariff rates encourages high productivity plants to start importing more than low productivity plants. Column (2) uses three input tariff dummies,  $D_{\tau_m,1}$ ,  $D_{\tau_m,2}$ , and  $D_{\tau_m,3}$ , in place of input tariff rate  $\tau_m$ . The interaction terms of  $D_{\tau_m,1}$ ,  $D_{\tau_m,2}$ , and  $D_{\tau_m,3}$  with labor productivity are significantly positive; since the highest range of tariff rates is set to be a baseline, this also indicates that the effect of a reduction of input tariff rates on importing is positively related to plant productivity. Adding more plant-level controls in column (3) does not change the main result; the interaction terms between labor productivity and tariff dummies are significantly positive with additional controls of R&D, Training, and capital per worker. Overall, these results confirm that our instruments for import decision are not weak.

Columns (4)-(6) of Table 3 provide the results from the logit of exporting decision. As in the case of import decision, the interaction terms between labor productivity and output tariff rate or output tariff dummies are significant and have the expected sign, indicating that a reduction of output tariff rates has a positive impact on exporting, especially among highly productive firms.

## 4.2 Estimation of the Impact of Importing and Exporting on Skill Demand

Table 4 reports the results from estimating skill demand equation (4) using three different methods: OLS, IV with the estimated probability of importing or exporting as instrument, and IV with tariff dummies and their interactions with labor productivity as instrument. The dependent variable is the logarithm of the ratio of the number of workers with more than high-school degree to the number of workers with less than high-school degree, where education-level is adjusted within each category of skilled and unskilled labors.

As shown in Columns (1)-(6) of Table 4, the impact of importing on skill demand is significantly positive across three different methods and different sets of controls. The IV estimates in Columns (3)-(4) or (5)-(6) are substantially larger than their OLS counterparts. The presence of unobserved heterogeneous response may be responsible for this result; as argued in Imbens and Angrist (1994) and Card (2001), when  $\beta$  in skill demand equation (4) is heterogeneous across firms, the IV estimator will give the weighted average of the impact of importing on skill demand across plants that switch their import status due to a change in the value of instruments.

On the other hand, in Column (9)-(12) of Table 4, the IV estimates of the effect of exporting on skill demand is not significant although the OLS estimates in Column (7)-(8) are significantly positive. One possible explanation is that, to take advantage of low wage for unskilled labor in Indonesia, exporting may encourage plants to adopt skill-scarce technology or to switch their products toward skill-scarce products, canceling the positive effect of exporting on skill demand from the adoption of skill-biased foreign technology.

Table 5 reports the IV estimates of skill demand equation (4) separately for five different set of subsamples classified by the estimated probability of importing or exporting conditional on observable characteristics, where  $\hat{P}(D_m = 1)$  and  $\hat{P}(D_x = 1)$  are the estimated probabilities of importing and exporting obtained from the specifications in Columns (3) and (6) of Table 3, respectively. The IV regressions applied to the subsamples use tariff dummies and their interactions with labor productivity as instruments and include a full set of controls as reported in Columns (6) and (12) of Table 4.

As reported in the second column of Table 5, the IV estimates of the impact of importing are larger for plants with less 10 percent of importing probability than for those with more than 10 percent of importing probability. This result suggests the presence of unobserved heterogeneous response. Namely, plants with observable characteristics that lead to low probability of

importing would be induced to start importing by the instruments only if they expect a large gain from importing. Thus, for plants with low value of  $\hat{P}(D_m = 1)$ , the marginal plants who would be induced to start importing by the instruments must have high ability to adopt foreign skill-biased technology and their coefficients of  $D_m$  would be high. Similarly, in the sixth column of Table 6, the IV estimates of the impact of exporting on skill demand are larger for plants with low probability of exporting than those with high probability of exporting, suggesting the presence of unobserved heterogeneous response of exporting on skill demand.

To further examine the possibility of heterogeneous impact of importing on skill demand, we follow the methodology suggested by Heckman and Vytlacil and estimate the marginal treatment effect (MTE) to compute the TT, the ATE, and the TUT.

Figures 1 and 2 show the MTE of importing and exporting, respectively, on skill demand, where the dotted lines indicate the 90 percent bootstrap confidence interval. In Figure 1, the MTE of importing on skill demand is decreasing in the value of  $U_D$  that makes plants to be indifferent between importing and not importing. That is, for a plant with low probability of importing conditional on observable variables (i.e., low  $U_D$ ), the high value of unobserved heterogeneous response  $\beta$  is necessary for the firm to self-select into importing. The observed downward sloping MTE is evidence for unobserved response heterogeneity; if there is no unobserved heterogeneity in the impact of importing, the slope of the MTE would be flat. On the other hand, in Figure 2, the MTE of exporting is not downward sloping, providing little evidence for unobserved heterogeneity in the impact of exporting.

Table 6 shows the TT, the ATE, and the TUT of importing and exporting computed from the estimated MTE with different weighting functions. In the first row of Table 6, the TT, the ATE, and the TUT of importing are significantly positive with point estimates of 10.54, 0.86, and 0.67, respectively. The magnitude of the TT is much larger than the ATE and the TUT, indicating that importing plants self-select into importing because their gain from importing is larger than the gain for non-importing plants. The small value of the TUT suggests that a further reduction of importing tariff rates in Indonesia would have a relatively small impact on skill demand because those plants that are not currently importing are the ones with low values of  $\beta$ .

On the other hand, as the second row of Table 6 reports, the TT, the ATE, and TUT of exporting on skill demand are not significant, and the point estimates of the ATE and the TUT are even negative. Thus, our analysis on the impact of exporting on skill demand using the framework of MTE provides evidence neither for the positive impact of exporting on skill demand nor for the presence of heterogeneous impact of exporting.

We also examine how importing and exporting induces an increase in the demand for skill within production workers or within non-production workers. When we examine the skill demand equation within production workers, since education level of production workers is low, we define workers with at least junior high-school degree as skilled labor and those without junior high-

school degree as unskilled labor.

Table 7 shows the TT, the ATE, and the TUT of importing and exporting within production workers and within non-production workers. As shown in the first row of Table 7, the TT of importing is substantially larger than the ATE and the TUT for both within production workers and non-production workers although both the ATE and the TUT are also significantly positive at 5 percent. Thus, the effect of importing on skill demand is strong, especially for plants that choose to import, both within production workers and within non-production workers.

On the other hand, as reported in the second row of Table 7, there is an interesting difference in the effect of exporting on skill demand between within production workers and within non-production workers; the TT, the ATE, and the TUT of exporting on skill demand within production workers are not significant with negative point estimates while the treatment effects of exporting within non-production workers are all significantly positive. This result suggests that exporting leads to skill upgrading within non-production workers but it does not necessarily increase the skill demand for production workers.

## 5 Concluding Remark

This paper empirically examines the effect of importing and exporting on skill demand using the Indonesian manufacturing data set that contains the detailed plant-level information on worker's education level. With input and output tariffs at 5-digit industry level as instruments for endogenous import and export decisions, we estimate the skill demand equation to quantify the causal effect of importing and exporting on skill demand. Using the framework developed by Heckman and Vytlacil, we allow for a possibility that the impact of importing and exporting on skill demand is heterogeneous across plants and estimate the treatment effect on the treated (TT), the average treatment effect (ATE), and the treatment effect on the untreated (TUT) separately for within production workers and within non-production workers.

The results suggest that the effect of importing on skill demand is large while the evidence for the positive effect of exporting on skill demand is mixed. Importing increases skill demand for both within production workers and non-production workers. Furthermore, we find that the effect of importing on skill demand among importers (TT) is substantially larger than that of importing among non-importers (TUT), suggesting that importers self-select into importing because their gains from importing is large. Our results also indicate that exporting induces skill-upgrading within non-production workers, especially for plants that choose to export. We do not find, however, any supportive evidence for the positive effect of exporting on skill-upgrading within production workers. Thus, a plant that starts exporting may employ more educated non-production workers but it does not necessarily employ more production workers who are educated.

## 6 Appendix: Estimation of MTE, ATE, TT, and TUT

Heckman and Vytlacil (2005) shows that the MTE defined in (9) can be identified by the derivative of  $E[S|X = x, P(Z) = p]$  with respect to  $p$  as follows. First write the skill demand equation as  $S = DS_1 + (1 - D)S_0 = \mu_0(X) + D[\mu_1(X) - \mu_0(X)] + U_0 + D(U_1 - U_0)$ . We assume that  $(U_1, U_0)$  is independent of  $X$ . Taking the conditional expectation of  $S$  given  $X$  and  $P(Z)$ , and noting that  $E[D|X, P(Z)] = P(Z)$ , we have

$$E[S|X, P(Z)] = \mu_0(X) + P(Z)[\mu_1(X) - \mu_0(X)] + E[U_1 - U_0|U_D \leq P(Z)]P(Z).$$

Then, the MTE can be identified within the support of  $P(Z)$  as

$$\Delta^{MTE}(x, p) = \left. \frac{\partial E[S|X, P(Z)]}{\partial P(Z)} \right|_{X=x, P(Z)=p} = \mu_1(x) - \mu_0(x) + E[U_1 - U_0|U_D = p].$$

The term  $\mu_1(x) - \mu_0(x)$  represents the component of the MTE depending on  $X$  while  $E[U_1 - U_0|U_D = p]$  represents the component of the MTE that depends on  $U_D$ .

To estimate the MTE, we impose the linear function form of  $\mu_0(X) = \alpha_0 + X\beta'_0$  and  $\mu_1(X) = \alpha_1 + X\beta'_1$ , where  $\alpha_0$  and  $\alpha_1$  represent the intercept terms. Then,

$$E[S|X, P(Z)] = \alpha_0 + P(Z)\Delta\alpha + X\beta'_0 + P(Z)X\Delta\beta' + E[U_1 - U_0|U_D \leq P(Z)]P(Z), \quad (10)$$

where  $\Delta\alpha = \alpha_1 - \alpha_0$  and  $\Delta\beta = \beta_1 - \beta_0$ . This suggests that  $\beta_0$  and  $\Delta\beta$  can be estimated by a partially linear regression of  $S$  on  $X$  and  $P(Z)$ . The easiest way to do this is to approximate  $E[U_1 - U_0|U_D \leq P(Z)]P(Z)$ , say, by a fourth order polynomials in  $P(Z)$  as  $E[U_1 - U_0|U_D \leq P(Z)]P(Z) \approx \rho_0 + \rho_1 P(Z) + \rho_2 (P(Z))^2 + \rho_3 (P(Z))^3 + \rho_4 (P(Z))^4$ .<sup>8</sup> While we are not able to separately identify  $\alpha_0$  and  $\Delta\alpha$  from the intercept and the linear term of  $E[U_1 - U_0|U_D \leq P(Z)]P(Z)$ , we are able to identify the MTE as follows. We first estimate  $P(Z)$  by a logit regression of  $D$  on polynomials in  $Z$ . In the second step, we run OLS of  $S$  on constant,  $X$ ,  $\hat{P}(Z)X$ , and  $\hat{P}(Z)$ ,  $(\hat{P}(Z))^2$ ,  $(\hat{P}(Z))^3$ , and  $(\hat{P}(Z))^4$ :

$$S = (\alpha_0 + \rho_0) + X\beta'_0 + \hat{P}(Z)X\Delta\beta' + (\rho_1 + \Delta\alpha)\hat{P}(Z) + \rho_2(\hat{P}(Z))^2 + \rho_3(\hat{P}(Z))^3 + \rho_4(\hat{P}(Z))^4 + v.$$

Once  $E[S|X, P(Z)]$  is estimated, then we may take a derivative with respect to  $P$  to estimate the MTE as

$$\hat{\Delta}^{MTE}(x, p) = x\hat{\Delta}\beta' + (\rho_1 + \hat{\Delta}\alpha) + 2\hat{\rho}_2 p + 3\hat{\rho}_3 p^2 + 4\hat{\rho}_4 p^3.$$

We use bootstrap to construct confidence interval bands for  $\hat{\Delta}^{MTE}$ .

<sup>8</sup>An alternative to polynomial approximation is local quadratic estimator as suggested in footnote 17, page 17, of Carneiro, Heckman, and Vytlacil (2006).

The Average Treatment Effect is computed as

$$ATE(x) = \int_0^1 \Delta^{MTE}(x, p) dp = x\hat{\Delta}\beta' + (\rho_1 + \hat{\Delta}\alpha) + \hat{\rho}_2 + \hat{\rho}_3 + \hat{\rho}_4.$$

The treatment effect for a firm with  $(X, Z) = (x, z)$  who decides to export or import is

$$TT(x, P(z)) = E[S_1 - S_0 | X = x, D = 1] = E[S_1 - S_0 | X = x, U_D \leq P(z)].$$

Since the probability density function of  $U_D$  conditional on  $U_D \leq P(z)$  is  $1/P(z)$ , we may write

$$\begin{aligned} TT(x, P(z)) &= \int_0^{P(z)} E[S_1 - S_0 | X = x, U_D = p] \frac{1}{P(z)} dp \\ &= \int_0^{P(z)} \Delta^{MTE}(x, p) \frac{1}{P(z)} dp \end{aligned}$$

The average impact of treatment on firms who actually export or import (TT) is computed by integrating out  $P(z)$  from the  $TT(x, P(z))$  using the distribution of  $P(Z)$  conditional on  $X = x$  and  $D = 1$ , denoted by  $f_{P(Z)|X, D=1}$ , as:

$$\begin{aligned} TT(x) &= \int_0^1 \left[ \int_0^{P(z)} \Delta^{MTE}(x, p) \frac{1}{P(z)} dp \right] f_{P(Z)|X, D}(P(z) | X = x, D = 1) dP(z) \\ &= \frac{1}{\Pr(D = 1 | X = x)} \int_0^1 \left[ \int_0^{P(z)} \Delta^{MTE}(x, p) dp \right] f_{P(Z)|X}(P(z) | X = x) dP(z) \end{aligned}$$

where the second equality follows from applying the Bayes' rule as  $f_{P(Z)|X, D}(P(z) | X = x, D = 1) = \frac{\Pr(D=1|X=x, P(Z)=P(z))}{\Pr(D=1|X=x)} f_{P(Z)|X}(P(z) | X = x) = \frac{P(z)}{\Pr(D=1|X=x)} f_{P(Z)|X}(P(z) | X = x)$ . Heckman and Vytlacil (p.5100, 2007) shows that the right hand side of the above equation can be rewritten as

$$TT(x) = \int_0^1 \Delta^{MTE}(x, p) \omega_{TT}(x, p) dp$$

with

$$\omega_{TT}(x, p) = \frac{1 - F_{P(Z)|X}(p|x)}{\int_0^1 [1 - F_{P(Z)|X}(t|x)] dt} = \frac{\Pr(P(Z) > p | X = x)}{E[P(Z) | X = x]},$$

where  $F_{P(Z)|X}$  is the distribution function of  $P(Z)$  conditional on  $X$ . When the dimension of  $Z$  conditioning  $X = x$  is small and the sample size is sufficiently large at  $X = x$ , it is straightforward to estimate  $\Pr(P(Z) > p | X = x)$  and  $E[P(Z) | X = x]$ . For instance, if there is only one instrument (i.e.,  $\dim(Z) = \dim(X) + 1$ ), then we can just use a sample frequency or its smoothed version.<sup>9</sup>

<sup>9</sup>In practice,  $P(Z)$  often have a limited support so that we would like to integrate over the region, say,  $[0.05, 0.95]$  (see p. 22 of Carneiro et al.). Further, as Appendix E of Carneiro et al. discusses, we need to integrate out  $x$

The average impact of treatment on firms that choose not to export or import (TUT) is

$$TUT(x) = \int_0^1 \Delta^{MTE}(x, p) \omega_{TUT}(x, p) dp$$

with  $\omega_{TUT}(x, p) = \frac{\Pr(P(Z) \leq p | X=x)}{E[1-P(Z) | X=x]}$ .

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using the conditional distribution of  $x$  given  $D = 1$ . In the current version, we partition the space of  $P(Z)$  into finite bins over the region  $[0.05, 0.95]$  and use a sample frequency to integrate out  $p$  across those bins.

## References

- Amiti, Mary, and Donald Davis (2008) "Trade, Firms, and Wages: Theory and Evidence," NBER Working Papers 14106.
- Amiti, Mary, and Jozef Konings (2008) "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Reviews*.
- Attanasio, O., Goldberg P., and N. Pavcnik (2004) "Trade Reforms and Wage Inequality in Colombia," *Journal of Development Economics* 74: 331-366.
- Autor, D., L. Katz, and A. Krueger (1998) "Computing Inequality: Have Computers Changed the Labor Market," *Quarterly Journal of Economics*, 113: 1169-1214.
- Baily, Martin N., Hulten, Charles, and David Campbell (1992) "Productivity Dynamics in Manufacturing Plants," *Brookings Papers on Economic Activity: Microeconomics*, 67-119.
- Berman, E., Bound, J., Grilliches, Z. (1994) "Changes in the Demand for Skilled Labour within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," *Quarterly Journal of Economics* 109: 367-397.
- Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum (2003) "Plants and Productivity in International Trade," *American Economic Review*, 93(4): 1268-1290.
- Bernard, Andrew B. and J. Bradford Jensen (1999) "Exporters, Skill Upgrading, and the Wage Gap," *Journal of International Economics*, 42: 1-25.
- Biscourp, P. and F. Kramarz (2007) "Employment, Skill Structure and International Trade: Firm-level Evidence for France," *Journal of International Economics*, 72(1): 22-51.
- Bustos, Paula (2007) "The Impact of Trade on Technology and Skill Upgrading: Evidence from Argentina," mimeo, University of Pompeu Fabra.
- Card, David (2001) "Estimating the Return to Schooling: Progress on some Persistent Econometric Problems" *Econometrica* 69(5): 1127-1160.
- Card, David, John E. DiNardo (2002) "Skill Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles," *Journal of Labor Economics*, 20: 733-783.
- Carneiro, P., J.J. Heckman, and E. Vytlacil (2006) "Estimating Marginal and Average Returns to Education," mimeo, University of College London.
- Clerides, Sofronis, Lach, Saul, and James R. Tybout (1998) "Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco," *Quarterly Journal of Economics* 113: 903-947.

- Doms, Mark, Timothy Dunne, and Kenneth R. Troske (1997) "Workers, Wages, and Technologies," *Quarterly Journal of Economics*, 112: 253-290.
- Duflo, Esther (2001) "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment," *American Economic Review*, 91(4): 795-813.
- Gindling, T.H., Robbins, D. (2001) "Patterns and Sources of Changing Wage Inequality in Chile and Costa Rica During Adjustment," *World Development*, 29: 725-745.
- Goldberg, P.K. and N. Pavcnik (2007) "Distributional Effects of Globalization in Developing Countries," *Journal of Economic Literature*, Vol. XLV, pp. 3982
- Griliches, Zvi (1969) "Capital-Skill Complementarity," *Review of Economics and Statistics*, 51: 465-468.
- Halpern, László, Miklós Koren, and Adam Szeidl (2006) "Imports and Productivity," mimeo, Federal Reserve Bank of New York.
- Harrison, Ann, and Gordon Hanson (1999) "Who Gains from Trade Reform? Some Remaining Puzzles," *Journal of Development Economics*, 59: 125-154.
- Heckman, J.J. (1979) "Sample Selection Bias as a Specification Error," *Econometrica* 47: 153-161.
- Heckman, J.J., and E.J. Vytlacil (1999) "Local Instrumental Variables and latent Variable models for Identifying and Bounding Treatment Effects" *Proceedings of the National Academy of Sciences* 96: 4730-4734.
- Heckman, J.J., and E.J. Vytlacil (2005) "Structural Equations, Treatment Effects and Econometric Policy Evaluation," *Econometrica* 73(3): 669-738.
- Heckman, J.J., and E.J. Vytlacil (2007a) "Econometric Evaluation of Social Programs, Part I: Causal Models, Structural Models and Econometric Policy Evaluation" in Heckman, J. and E. Leamer (Eds.), *Handbook of Econometrics*, vol. 6B. North-Holland, New York:: 4780-4874.
- Heckman, J.J., and E.J. Vytlacil (2007b) "Econometric Evaluation of Social Programs, Part II: Using the Marginal Treatment Effect to Organize Alternative Econometric Estimators to Evaluate Social Programs, and To Forecast their Effects in New Environments" in Heckman, J. and E. Leamer (Eds.), *Handbook of Econometrics*, vol. 6B. North-Holland, New York:: 4875-.
- Imbens, Guido, and Joshua Angrist (1994) "Identification and Estimation of Local Average Treatment Effects," *Econometrica* 62(2): 467-475.

Kasahara, Hiroyuki and Beverly Lapham (2008) "Productivity and the Decision to Import and Export: Theory and Evidence," CESifo Working Paper.

Kasahara, H. and J. Rodrigue (2008) "Does the Use of Imported Intermediates Increase Productivity? Plant-level Evidence," *Journal of Development Economics* 87: 106-118.

Lileeva, Alla, and Daniel Trefler (2007) "Improved Access to Foreign Markets Raises Plant-Level Production...For Some Plants" NBER Working Paper 13297.

Kugler, M. and E. Verhoogen (2009) "Plants and Imported Inputs: New Facts and an Interpretation," *American Economic Review Papers and Proceedings*, forthcoming.

Melitz, Mark J.(2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71: 1695-1725.

Muendler, Marc-Andreas (2004) "Trade, Technology, and Productivity: A Study of Brazilian Manufacturers, 1986-1998," UCSD, mimeo.

Pavcnik, Nina (2002) "Trade Liberalization, Exit, and Productivity Improvements: Evidence From Chilean Plants," *Review of Economic Studies*, 69(1): 245-276.

Pavcnik, Nina (2003) "What explains skill upgrading in less developed countries?" *Journal of Development Economics* 71: 311-328.

Pavcnik, N., A. Blom, P. Goldberg and N. Schady (2004) "Trade liberalization and industry wage structure: evidence from Brazil," *World Bank Economic Review*, 18: 319-344.

Sanchez-Paramo, C. and N. Schady (2003): "Off and Running? Technology, Trade, and the Rising Demand for Skilled Workers in Latin America," *World Bank Policy Research Working Paper* 3015. Washington, DC: World Bank.

Table 1: Descriptive Statistics: Trade and Skill Intensity 1996-1997, All Workers

Trade	Owner -ship	Highest Degree Completed/Fraction						Training Worker	R& D Worker	Non-Prod. All Workers	No. of Obs.
		No Primary	Jr. Primary	High High	High High	College	Grad. School				
No-Ex/No-Im	All	0.108	0.430	0.235	0.208	0.018	0.0003	0.024	0.024	0.132	29153
Ex/No-Im	All	0.068	0.310	0.264	0.329	0.029	0.0005	0.077	0.116	0.152	4184
No-Ex/Im	All	0.042	0.264	0.239	0.395	0.058	0.001	0.180	0.254	0.202	5091
Ex/Im	All	0.021	0.165	0.249	0.502	0.062	0.001	0.212	0.315	0.175	2356
All	All	0.091	0.382	0.239	0.261	0.027	0.0005	0.060	0.079	0.145	40784
No-Ex/No-Im	For.	0.040	0.198	0.221	0.475	0.066	0.0006	0.241	0.161	0.231	369
Ex/No-Im	For.	0.047	0.211	0.243	0.452	0.046	0.0004	0.049	0.257	0.172	332
No-Ex/Im	For.	0.011	0.106	0.181	0.591	0.109	0.002	0.576	0.829	0.258	755
Ex/Im	For.	0.011	0.105	0.198	0.605	0.080	0.002	0.283	0.594	0.182	935
All	For.	0.020	0.134	0.202	0.559	0.082	0.002	0.337	0.555	0.212	2391
No-Ex/No-Im	Dom.	0.109	0.433	0.235	0.204	0.018	0.0003	0.022	0.022	0.131	28784
Ex/No-Im	Dom.	0.070	0.318	0.266	0.318	0.027	0.0005	0.079	0.104	0.150	3852
No-Ex/Im	Dom.	0.048	0.292	0.249	0.361	0.049	0.001	0.111	0.153	0.192	4336
Ex/Im	Dom.	0.028	0.204	0.283	0.434	0.049	0.001	0.166	0.131	0.170	1421
All	Dom.	0.095	0.397	0.242	0.242	0.023	0.0004	0.043	0.049	0.141	38393

Notes: Standard deviations are in parentheses. The first column indicates import and export status, where “No-Ex/No-Im” denotes plants that neither export nor import; “Ex/No-Im” denotes plants that exports but do not import; “No-Ex/Im” denotes plants that do not export but import; and “Ex/Im” denotes plants that both import and export. The second column indicates whether plants are owned by foreign investors, where “For.” denotes plants for which at least 10% of equity is held by foreign investors while “Dom.” denotes plants for which at least 90 % of equity is held by domestic investors.

Table 2: Descriptive Statistics: Trade and Skill Intensity 1996-1997, Production vs. Non-Production Workers

Trade	Owner -ship	Production Workers				Non-Production Workers				Frac. of Plants Without Any Non-prod. workers
		Less than Primary	Jr. High	High High	College Grad.	Less than Primary	Jr. High	High High	College Grad.	
No-Ex/No-Im	All	0.569	0.246	0.178	0.007	0.187	0.192	0.524	0.098	0.254
Ex/No-Im	All	0.408	0.283	0.297	0.012	0.112	0.140	0.587	0.159	0.102
No-Ex/Im	All	0.333	0.260	0.380	0.027	0.101	0.143	0.553	0.203	0.102
Ex/Im	All	0.201	0.269	0.501	0.030	0.076	0.128	0.547	0.250	0.030
All	All	0.501	0.253	0.234	0.011	0.158	0.174	0.537	0.131	0.206
No-Ex/No-Im	For.	0.254	0.236	0.483	0.028	0.110	0.152	0.493	0.245	0.073
Ex/No-Im	For.	0.279	0.259	0.438	0.024	0.107	0.125	0.539	0.228	0.042
No-Ex/Im	For.	0.127	0.198	0.627	0.047	0.076	0.107	0.492	0.325	0.025
Ex/Im	For.	0.123	0.212	0.627	0.039	0.064	0.108	0.526	0.301	0.027
All	For.	0.166	0.218	0.578	0.038	0.081	0.117	0.512	0.290	0.036
No-Ex/No-Im	Dom.	0.573	0.246	0.174	0.007	0.188	0.192	0.524	0.096	0.256
Ex/No-Im	Dom.	0.419	0.285	0.285	0.011	0.113	0.142	0.592	0.153	0.107
No-Ex/Im	Dom.	0.369	0.271	0.337	0.023	0.106	0.149	0.564	0.180	0.115
Ex/Im	Dom.	0.251	0.306	0.418	0.024	0.084	0.141	0.561	0.215	0.032
All	Dom.	0.523	0.255	0.213	0.010	0.163	0.179	0.539	0.119	0.217

Notes: Standard deviations are in parentheses. The first column indicates import and export status, where “No-Ex/No-Im” denotes plants that neither export nor import; “Ex/No-Im” denotes plants that exports but do not import; “No-Ex/Im” denotes plants that do not export but import; and “Ex/Im” denotes plants that both import and export. The second column indicates whether plants are owned by foreign investors, where “For.” denotes plants for which at least 10% of equity is held by foreign investors while “Dom.” denotes plants for which at least 90 % of equity is held by domestic investors.

Table 3: Logit of the Probability of Importing and Exporting using tariff level as instruments

Dependent Variable:	Import Status			Export Status		
	(1)	(2)	(3)	(4)	(5)	(6)
$\tau$	11.969 (1.657)			2.988 (0.467)		
Labor Prod $\times \tau$	-1.778 (0.349)			-0.311 (0.104)		
$D_{\tau,1}$		-2.531 (0.188)	-2.336 (0.190)		-1.572 (0.182)	-1.324 (0.180)
$D_{\tau,2}$		-2.017 (0.194)	-1.833 (0.196)		-1.361 (0.186)	-1.173 (0.183)
$D_{\tau,3}$		-3.243 (0.373)	-2.943 (0.375)		-1.953 (0.255)	-1.705 (0.252)
Labor Prod $\times D_{\tau,1}$		0.520 (0.042)	0.457 (0.041)		0.344 (0.039)	0.286 (0.038)
Labor Prod $\times D_{\tau,2}$		0.397 (0.042)	0.330 (0.041)		0.222 (0.038)	0.174 (0.037)
Labor Prod $\times D_{\tau,3}$		0.473 (0.079)	0.394 (0.079)		0.283 (0.052)	0.219 (0.051)
Labor Prod	0.664 (0.037)	0.076 (0.036)	0.010 (0.035)	0.464 (0.021)	0.182 (0.031)	0.121 (0.030)
Foreign	1.798 (0.055)	1.817 (0.056)	1.576 (0.058)	1.566 (0.053)	1.562 (0.053)	1.336 (0.055)
R&D			0.340 (0.053)			0.282 (0.056)
Training			0.708 (0.044)			0.695 (0.045)
Capital/Worker			0.194 (0.017)			0.171 (0.019)
No. of Obs.	39030	39030	39030	39030	39030	39030

Notes: Standard errors are in parentheses. 3-Digit Industry Effects and Year effects are included. When import decision is estimated, we use  $\tau = \tau_m$ ,  $D_{\tau,1} = D_{\tau_m,1} = 1(0.085 \leq \tau_m < 0.156)$ ,  $D_{\tau,2} = D_{\tau_m,2} = 1(0.037 \leq \tau_m < 0.085)$ , and  $D_{\tau,3} = D_{\tau_m,3} = 1(\tau_m < 0.037)$ ; when export decision is estimated, we use  $\tau = \tau_x$ ,  $D_{\tau,1} = D_{\tau_x,1} = 1(0.150 \leq \tau_x < 0.238)$ ,  $D_{\tau,2} = D_{\tau_x,2} = 1(0.048 \leq \tau_x < 0.150)$ , and  $D_{\tau,3} = D_{\tau_x,3} = 1(\tau_x < 0.048)$ .

Table 4: Skill Demand Equation, All Workers

Dependent Variable: $\log((\text{High school Grad})/(\text{Less than High school}))$												
	OLS		IV with $\hat{P}(D_m = 1)$		IV with $\tau_m$ 's		OLS		IV with $\hat{P}(D_x = 1)$		IV with $\tau_x$ 's	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Import Status	0.404 (0.021)	0.293 (0.021)	2.053 (0.186)	1.239 (0.151)	2.371 (0.329)	0.983 (0.142)						
Export Status							0.298 (0.021)	0.213 (0.020)	-0.292 (0.152)	-0.401 (0.138)	0.214 (0.271)	0.257 (0.250)
Labor Prod	0.339 (0.007)	0.241 (0.008)	0.233 (0.014)	0.196 (0.011)	0.212 (0.022)	0.208 (0.010)	0.351 (0.007)	0.248 (0.008)	0.379 (0.011)	0.270 (0.009)	0.355 (0.015)	0.246 (0.012)
Foreign	0.767 (0.035)	0.563 (0.035)	0.171 (0.076)	0.260 (0.060)	0.056 (0.126)	0.342 (0.057)	0.824 (0.035)	0.600 (0.035)	1.000 (0.057)	0.763 (0.051)	0.849 (0.087)	0.588 (0.075)
R&D		0.151 (0.027)		0.098 (0.029)		0.113 (0.028)		0.161 (0.027)		0.181 (0.027)		0.159 (0.028)
Training		0.423 (0.023)		0.312 (0.029)		0.342 (0.028)		0.435 (0.023)		0.500 (0.027)		0.430 (0.035)
Capital/Worker		0.234 (0.008)		0.211 (0.009)		0.217 (0.009)		0.238 (0.009)		0.247 (0.009)		0.237 (0.009)
No. of Obs.	30479	30479	30479	30479	30479	30479	30479	30479	30479	30479	30479	30479

Notes: Standard errors are in parentheses. 3-Digit Industry Effects and Year effects are included. For the sixth and the seventh columns, import status is instrumented with  $D_{\tau_m,1}$ ,  $D_{\tau_m,2}$ ,  $D_{\tau_m,3}$ , and their interaction terms with Labor Prod. For the last two columns, export status is instrumented with  $D_{\tau_x,1}$ ,  $D_{\tau_x,2}$ ,  $D_{\tau_x,3}$ , and their interaction terms with Labor Prod.

Table 5: Some Evidence for Heterogeneous Impact of Importing on Skill Demand

Dependent Variable: $\log((\text{High school Grad})/(\text{Less than High school}))$							
Subsample	Coefficient on $D_m$		No. of Obs.	Subsample	Coefficient on $D_x$		No. of Obs.
	IV with $\tau_m$ 's	OLS			IV with $\tau_x$ 's	OLS	
$\hat{P}(D_m = 1) \leq 0.05$	4.763 (1.634)	0.389 (0.068)	7095	$\hat{P}(D_x = 1) \leq 0.05$	9.817 (3.359)	0.201 (0.096)	6242
$0.05 < \hat{P}(D_m = 1) \leq 0.10$	2.681 (0.885)	0.352 (0.063)	4946	$0.05 < \hat{P}(D_x = 1) \leq 0.10$	5.554 (1.668)	0.220 (0.061)	6625
$0.10 < \hat{P}(D_m = 1) \leq 0.25$	1.505 (0.564)	0.244 (0.037)	9931	$0.10 < \hat{P}(D_x = 1) \leq 0.25$	1.132 (0.415)	0.310 (0.034)	10025
$0.25 < \hat{P}(D_m = 1) \leq 0.45$	0.874 (0.473)	0.248 (0.040)	4737	$0.25 < \hat{P}(D_x = 1) \leq 0.45$	0.905 (0.284)	0.161 (0.036)	5059
$0.45 < \hat{P}(D_m = 1) \leq 0.65$	1.887 (0.555)	0.386 (0.063)	1853	$0.45 < \hat{P}(D_x = 1) \leq 0.65$	-0.193 (0.886)	0.068 (0.070)	1853
$0.65 < \hat{P}(D_m = 1)$	-4.524 (1.965)	0.126 (0.082)	1917	$0.65 < \hat{P}(D_x = 1)$	0.543 (1.352)	0.068 (0.118)	776

Notes: Standard errors are in parentheses. The estimated coefficients on import status  $D_m$  or export status  $D_x$  are reported for different set of subsamples classified by the estimated probability of importing or importing. Other variables included in the regression are: Labor Prod, Foreign, R&D, Training, Capital/Worker, 3-Digit Industry Effects, and Year effects.

Table 6: TT, ATE, and TUT of Importing and Exporting on Skill Demand, All Workers

	TT	ATE	TUT
Importing	10.536 (1.552)	0.862 (0.211)	0.671 (0.268)
Exporting	1.398 (2.206)	-0.204 (0.160)	-0.244 (0.153)

Table 7: TT, ATE, and TUT of Importing and Exporting on Skill Demand, Within Production Workers and Within Non-Production Workers

	Within Production Workers			Within Non-Production Workers		
	TT	ATE	TUT	TT	ATE	TUT
Importing	8.259 (1.637)	0.872 (0.299)	0.676 (0.370)	9.046 (1.680)	1.085 (0.426)	0.859 (0.327)
Exporting	-0.057 (2.380)	-0.571 (0.308)	-0.709 (0.320)	9.432 (2.309)	1.250 (0.323)	1.194 (0.337)

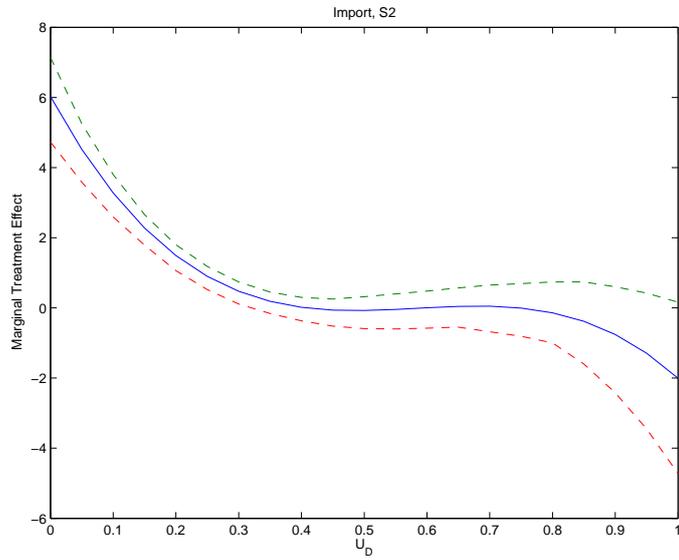


Figure 1: MTE of Importing on Skill Demand

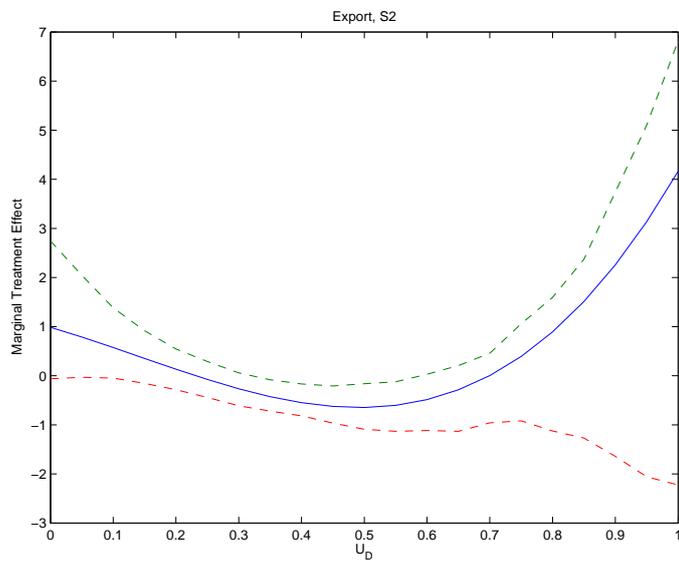


Figure 2: MTE of Exporting on Skill Demand