Does Importing Intermediates Increase the Demand for Skilled Workers? Plant-level Evidence from Indonesia

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Abstract

This paper examines whether importing has contributed to skill upgrading among Indonesian plants. Our data records the distribution of years of employee schooling in each plant. We examine how importing affects the demand for highly educated workers within both production and non-production occupation categories at the plant level. We estimate a model of importing and skill-biased technological change in which selection into importing arises due to unobservable heterogenous returns from importing. We find that importing has substantially increased the relative demand for educated production workers, but has had little impact on the demand for educated non-production workers.

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1 Introduction

Workhorse models of international trade almost universally suggest that increased integration into international markets will encourage resources to be reallocated towards workers, firms, or industries in which the country has a comparative advantage. In developing countries, for example, trade liberalization is often supported by the argument that trade will expand in labor-intensive industries which, in turn, are predicted to increase the relative demand and wages for unskilled labor. Surprisingly, in many contexts, exactly the opposite has been found. Numerous studies confirm that among developing countries, trade liberalization has increased the relative firm-level demand for skilled labour (Sanchez-Paramo and Schady, 2003; Goldberg and Pavcnik, 2007) and, likewise, has caused the skill premium to rise (Harrison and Hanson (1999), Gindling and Robbins (2001), Attanasio et al. (2004)).[1] Despite these stark trends, the underlying cause of the increased demand for skilled workers, the contribution from trade, and the implications for income inequality remain key, unresolved issues (Goldberg and Pavcnik, 2005).[2]

This paper contributes to this literature by examining the impact that importing foreign materials has on the demand for highly educated workers among Indonesian manufacturing plants. The idea that importing may affect firm organization or productivity is neither new or controversial. Rather, it is widely reported that using foreign intermediate goods in production often requires the plant-level adoption of more sophisticated technology.[3] The adoption of foreign technology, and thus importing in a developing country, is likely to induce further structural changes within individual manufacturing plants. In fact, there is a rich literature indicating that the reallocation of workers is strongly related to changes in the demand for skilled labour *within* firms, rather than across industries (Berman, Bound, and Griliches, 1994; Bernard and Jensen, 1997; and Biscourp and Kramarz, 2007). We extend this line of research by relating changes in the relative use of educated workers to observable decisions to import intermediate materials at the plant-level.

Our data are exceptionally well suited to this objective. Typically, researchers have used

[1] In contrast, Amiti and Cameron (2012) find that falling input tariffs has caused the wage skill premium within firms that import their intermediate inputs to fall.

[2] Our work is likewise related to studies of trade, employment and wages (Trefler, 2004; Gonsaga et al., 2006; Bernard et al, 2007; Egger and Kreikemeier, 2009; Davis and Harrigan, 2011; Felbermayr et al., 2011; Amiti and Davis, 2012), and trade, wages and the demand for skilled workers (Bernard and Jensen, 1997; Yeaple, 2005; Verhoogen, 2008; Frías et al., 2009; Chor, 2010; Helpman et al., 2010; Bustos, 2011; Cosar, 2011; Vannoorenberghe, 2011), and trade, wages and skill-biased technological change (Feenstra and Hanson, 1999; Matsuyama, 2007; Costinot and Vogel, 2010; Bloom et al., 2011; Burstein and Vogel, 2012; Burstein et al., 2013)

[3] This is particularly true when it is imported from industrialized nations for which there is substantial evidence of skill-biased technological change. 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. See Muendler (2004), Amiti and Konings (2007), Kasahara and Rodrigue (2008), Halpern, Koren, and Szeidl (2009), and Kugler and Verhoogen (2009) among others. There is also significant evidence that skill-biased technological change can increase the skill-premium even in developing countries (e.g., Kijima, 2006). Burstein et al. (2013) provide an alternative model whereby importing directly induces skill-biased technological change.

variation in occupation categories, such as non-production or white-collar workers, to construct a proxy for skilled labor (Bernard and Jensen, 1997; Harrison and Hanson, 1999; Pavcnik, 2003; Biscourp and Kramarz, 2007).[4] A major advantage of this study is that it is able to capture a much more precise measure skill at the plant-level. Specifically, the panel data record the education-level of every worker in every Indonesian manufacturing plant with at least 20 employees. Moreover, we are able to distinguish the distribution of worker education across non-production and production workers within each plant. This allows us to disentangle the impact of importing across broad occupation categories and more precisely characterize the effect of importing on firms in a developing country. We also evaluate the extent to which our results would have changed should we have used "conventional" measures of plant-level skill-intensity, the ratio of non-production workers to production workers, which ignores plant-level differences in skill and education within each occupation.

Quantifying the impact of importing on the demand for skilled labour requires overcoming a number of key empirical challenges. First, we are particularly concerned that the demand for skill and the decision to import are endogenously determined. We exploit detailed information capturing plant-level shipping costs to major Indonesian ports along with product-level tariff changes to identify the causal impact of importing on the demand for skilled labour. Using a variety of instrument sets we are able to capture robust IV estimates of the impact of importing on the demand for skilled labor.

Second, we are also concerned that the impact of trade on the demand for educated workers within plants will vary substantially across heterogeneous plants. For instance, importing foreign intermediate goods may provide plants with an incentive to hire more educated workers, but the degree of skill-upgrading may depend crucially on the plant's existing, potentially unobserved, heterogeneous ability to implement foreign technology. When the effect of importing on the demand for skill varies across plants, there is no single "effect" of importing on skill demand. Furthermore, we expect plants with greater ability to adopt technology will self-select into importing, leading to a difficult selection problem. In such cases, the instrumental variable (IV) estimator identifies the average effect of importing among plants induced to change their import status by the instrument (Imbens and Angrist, 1994). We also estimate the model by applying the treatment effect framework developed by Heckman and Vytlacil (2005, 2007a, 2007b) to identify various summary measures of the impact of importing on the relative demand

[4]Three important exceptions are Bustos (2011), Koren and Csillag (2011) and Frazer (2013). Using a panel of Argentinean manufacturing firms with the detailed information on worker's education level Bustos (2011) finds that exporting increases the demand for skilled labor, while our results suggest that importing, rather than exporting, is more important for skill upgrading. Using Hungarian linked employer-employee data, Koren and Csillag (2011) find that the wage gap between workers with a high school diploma and those with primary schooling is larger among workers operating imported machines than among workers operating domestic machines. Similarly, using linked data firm and employee data from Rwanda, Frazer (2013) studies the impact of importing intermediate inputs from low and high income countries on the average wages paid to Rwandan employees. While these studies focus on the effect of importing on the workers' wages, we examine the effect of importing on the relative employment of educated workers to less educated workers at plant-level.

for skilled labour in the Indonesian manufacturing sector, such as the average effect among all plants (the average treatment effect; the ATE, hereafter), the average effect among importers (the treatment effect on the treated; the TT, hereafter), and the average effect among non-importers (the treatment effect on the untreated; the TUT, hereafter).

Third, while we are able to identify the ATE, the TT and the TUT, it is unclear whether these objects are of particular interest to the policymaker. For instance, while the TT suggests that importing had an important impact on the demand for skilled labour among plants that were induced to import in our sample, it is unclear that further policy change will greatly affect the demand for skilled labour among new importers. We use the estimation framework of Carneiro, Heckman, and Vytlacil (2010) to study the impact of further policy changes on the demand for skilled labor among the set of plants induced to import by the change in policy.

On one hand, we find that importing has had a large impact on the demand for educated production workers among Indonesian manufacturing plants; across different specifications, our IV estimates suggest that starting to import strongly increases the demand for skilled labour among production workers. On the other hand, our IV estimates do not provide robust evidence for any impact of importing on skill upgrading among non-production workers. Our MTE estimates not only confirm that starting to import has strongly increased the demand for skilled production workers but also indicate that not all plants benefit equally from importing. We find that the ATE, the TT, and the TUT for production workers are significantly positive while the TT is estimated to be substantially larger than the ATE, which, in turn, is estimated to be larger than the TUT. Moreover, we find that further policy changes that promote importing would have substantially increased the demand for skilled production workers among the plants that would have been induced to start importing. In contrast, we rarely find any significant effect of importing on the skill composition of non-production workers in our estimates of various treatment effects. Finally, repeating our experiment ignoring the variation in worker education across plants, both our IV and MTE results suggest that the effect of importing on the ratio of non-production to production workers are insignificantly different from zero.

The next section describes our data set and documents the relationship between importing and plant-level skill-intensity. Section 3 describes our empirical model and the nature of selection. Section 4 describes the empirical results. The last section concludes.

2 Data

2.1 Data Sources

Our primary source of data is the Indonesian manufacturing survey between 1995 and 2007, where we mainly use the data recorded in the census years 1996 and 2006 because, in these two years, the Indonesian manufacturing survey records the distribution of academic achievement in two distinct occupation categories (non-production vs. production) in each plant. Specifically, in each plant we observe the number of workers with primary, secondary and post-secondary education. We use this information to construct the relative skill measures for each occupation category, which are directly based on the workers' education levels.

The manufacturing survey covers all manufacturing plants with at least 20 employees. In the 2006 data set, 93 percent of plants are also single-plant firms. The data set captures a wide set of plant-level characteristics which we use to study the nature of plant-level heterogeneity. In particular, the survey records all expenditures on imported intermediate materials which we use to identify the effect of importing on the demand for skilled labor. It also includes key plant-level input and output variables, such as total revenues, capital stock, domestic materials, necessary for computing plant-level productivity. Likewise, the survey records plant-level information including the percentage of sales from exports, the percentage of ownership held by foreign investors, total plant-level expenses on research and development (R&D), and total plant-level expenditures on worker training. Appendix A provides a detailed description of our variable construction.

Naturally, the extent to which a plant is willing to hire skilled workers depends heavily on the premium it must pay for that worker in its local labor market. Unfortunately, the manufacturing survey data do not provide a measure of wages by education level. To capture regional (city-level) variation in the skill premium we augment manufacturing survey with the Indonesian household survey. The Indonesian household survey covers a nationally representative sample of households. Each survey documents key labor force information including gender, age, location, educational attainment and labor force experience among a wide set of additional characteristics. We use the household survey to develop a measure of the skill premium in each location and year.

2.2 Importing and Worker Education

Panel A of Table 1 documents plant-level differences in employment across six education-based (highest attainment) categories: less than primary school, primary school, junior high school, high school, college graduates and post-graduate educated workers. The top panel compares the percentage of plant-level employment across importing and non-importing plants in 2006. We find that importing plants, on average, hire fewer workers in each educational category below high school and more workers with high-school diplomas, college degrees, or post-graduate training. For example, 61 percent of workers in importing plants have at least a high school degree, while only 36 percent of workers in non-importing plants have a high school degree or better. Columns (8)-(10) further compare associated measures of skill-intensity across importing and importing plants. "Training/Worker" and "R&D/Worker" report the average per worker expenditures on training and research and development (R&D), respectively, in thousands of 1983

Indonesian rupiahs while "Non-Prod./All Workers" reports the percentage of non-production workers in total employment in each plant. We find that the expenditures on training workers or investing in R&D among importers is more than double what is spent by non-importers on average. Likewise, importers tend to have a relatively large number of non-production workers in their plants. Each of these measures strongly suggests that importers are relatively skill-intensive manufacturing plants when compared to their non-importing counterparts.

Panel A of Table 1 also compiles similar statistics for exporting plants, non-exporting, domestic plants, and foreign-owned plants.[5] We observe a number of stark patterns: foreign plants tend to employ more skilled workers than domestic plants while exporting plants appear skill-intensive when compared to their non-exporting counterparts. Nonetheless, within each group we continue to find that importing plants hire a greater percentage of skilled workers, invest more heavily in R&D and worker training, and tend to use a greater percentage of non-production workers. Importantly, in any subgroup we begin to see large differences in the hiring patterns of importing plants at the high school level.

Panel B of Table 1 documents the percentage of total production or non-production employment in each educational category. Again, importing plants are found to systematically hire more workers with high school degrees or more and fewer workers with less education than high school within each of the two occupation categories. Although importers always appear to be more skill-intensive on average within each occupation category, the mechanism that drives the correlation between importing and skill-intensity may differ between production and non-production workers. While the use of imported materials might induce the adoption of new production processes which in turn requires hiring more skilled production workers, importing might require substantial increases in the number of non-production workers for trade related activities such as dealing with customs agents or arranging shipments from foreign countries. Given the potential for differences in the impact of importing on the demand for skilled workers across occupation categories, we attempt to disentangle the causal impact of importing on the demand for skilled workers within each occupation.

While Table 1 demonstrates the rich detail with which our data allow us to characterize the distribution of skill, they also point to a potentially important limitation. In particular, many Indonesian plants do not hire any workers with college or post-graduate training in both occupation categories. As a result, defining a skilled worker as a "college graduate" in this context would lead to eliminating a significant number of plants which are wholly composed of unskilled workers. For this reason, we choose to define a skilled worker as one with at least a high school degree. This definition not only allows us to better exploit the observed variation in our data, but is also the natural metric for skill given the context in which we conduct our empirical study. Indonesian high school graduates are exposed to greater logical and quantitative training (Hendayana et al, 2008). Further, the additional schooling allows high school students

[5] We classify a plant as foreign plant when at least 10 percent of its equity is held by foreign investors.

to refine their language skills in standard Indonesian (Bahasa Indonesia) and, for many, the opportunity to learn to communicate effectively in English (Kam, 2006). These communication skills are particularly important in this environment since Indonesian dialects vary widely across the country.

2.3 Instruments

We expect that the decision to import for any given plant is likely to be endogenously determined with its decision to hire skilled labour. The identification strategy we outline below relies on the presence of instruments. We consider three instruments: location-specific transport costs and changes in industry-specific input and output tariffs.

Since we do not observe transport costs to the port directly, we construct the measure of transport cost for each plant as follows. To incorporate geographical information, we first divide Indonesia into cells of one kilometer squared and assign a value of 1-10 to each cell, where "10" is the highest cost (Steepness of Slope, Sea vs. Land). Then, we use ArcGIS to find the least accumulative-cost path between any plant and its nearest port. Finally, our measure of transport cost is obtained from the least accumulative-cost after dividing it by the sample standard deviation.

For the second and the third instruments, we match each plant in our manufacturing survey to product-level (5-digit ISIC) output and input tariffs constructed by Amiti and Konings (2007). Full details of the construction of the transportation cost variable as well as further discussion on the tariff reduction can be found in Appendix A. We use the change in output and input tariff rates between 1996 and 2001 as our instrument. During our sample period Indonesia was broadly reducing tariffs across manufacturing industries.

We are concerned that the empirical estimates we find may be biased if the instruments we use are not exogenous. For the transport cost variable, it is possible that plants with a high-return from importing will choose to locate closer to ports. To deal with this potential concern for endogenous location choice, we also consider a sample of plants which initially did not import in 1996. In this fashion, we can consider the impact of transport costs (and tariffs) on plants who made their location decision well before they began using imported materials. For tariff changes, it is possible that tariff rate reductions are set to take advantage of industries where greater importing will have larger impact on technological adoption and the relative demand for skilled workers. As argued by Amiti and Konings (2007), however, an advantage of using the tariff rates during this period is that the reductions are largely driven by the fact that Indonesia is in the process of joining the WTO and, thus, are relatively likely to be exogenous to the broader political or economic environment. Nonetheless, in our IV regression, we also consider specifications which only use our transportation cost variable as the sole instrument to investigate whether the tariff rates potentially lead to biased estimates.

3 A Model of Importing and Skill-Biased Technology

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

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

where L_s is the number of skilled workers, L_u is the number of unskilled workers, $\sigma > 1$ is elasticity of substitution between skilled and unskilled workers, φ is a Hicks neutral productivity term, and A is a skilled labor augmenting technology term. For expositional transparency, we have purposefully kept the structure as simple as possible here. See Appendix C for our complete specification of the production function to estimate Hicks-neutral productivity φ.

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

$$S = (\sigma - 1)\ln A - \sigma \ln (W_s/W_u), \tag{2}$$

where W_s and W_u are the wages for skilled and unskilled workers, respectively.

To test whether importing increases the relative demand for skilled workers, we allow foreign imported inputs to affect the level of skilled labor augmenting technology as

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

where D is a dummy variable for the use of imported inputs, β is a parameter that captures the effect of importing on skill-biased technology A, X is a vector of observables, and U is a skill-biased technology shock. We can then write the relative demand for skilled workers as

$$S = D\beta + X\gamma' + U, \tag{4}$$

where, with abuse of notation, the second term on the right hand side of (2), $\ln (W_s/W_u)$, is incorporated into one of the variables in X.

While it is intuitive that importing is an endogenous decision because the import decision D and skill-biased technology shock U are likely to be correlated, it is also likely that the impact of importing on skill-biased technology and, thus, the demand for skilled labor will vary across heterogeneous plants. If we interpret the value of β as the ability for a plant to adopt skill-biased technology upon importing, the impact of importing on the demand for skilled workers would be heterogeneous whenever the plants' ability to adopt foreign technology is heterogeneous. This too has intuitive consequences for our simple specification: plants with a greater ability to adopt skilled-biased technology will self-select into importing because they will achieve larger productivity gains from importing. Because of this positive sorting on the unobserved gain from importing, we would expect that the value of β will be greater among plants that choose to import relative to non-importers.

To examine the nature of the potential bias arising from heterogeneous returns to importing we extend the benchmark model in (4) by assuming that the coefficient β varies across plants and we write $\beta = \bar{\beta} + \epsilon$, where $\bar{\beta}$ is the mean of β while ϵ is the plant-specific return to importing. We assume that ϵ is unobservable to the researcher but is, at least partially, known to the plant's manager. Then, equation (4) is written as

$$S = [\bar{\beta} + \epsilon]D + X\gamma' + U. \tag{5}$$

Imbens and Angrist (1994) show that, under certain conditions, using a single dummy instrument, an IV estimator identifies the local average treatment effect (LATE), or the average value of β among plants induced change their import choice by the instrument. When multiple dummy instruments are used, an IV estimator identifies a weighted average of the instrument-specific LATEs. Therefore, an IV estimator provides an estimate of an interpretable quantity even when the effect of importing on the demand for skilled workers is heterogenous across plants, although the LATE is generally different from the average value of β.

3.1 The Import Decision

To better understand how the plant-specific return to importing affects the plant's import decision, consider the following static import decision model. Each plant produces in monopolistically competitive markets with the demand function $q = B(Z)p^{-\eta}$, where q is the quantity demanded, p is the output price, $B(Z)$ is a demand shifter, η is the elasticity of substitution, and Z is a vector of observed variables containing X and other observables that serve as instruments. We assume constant returns to scale technology with the marginal cost determined by $c(A, \varphi) = \min_{\{L_s, L_u\}} w_s L_s + w_u L_u$ subject to $f(L_s, L_u, A, \varphi) \geq 1$. The skill biased technology term A depends on X and the import decision D as in (3) but we assume that importing does not affect the Hicks neutral technology level φ.[6] If the plant chooses to import, it incurs a fixed import cost $f_m(Z)$. Then plant's net profit function is $\pi(A, \varphi, Z, D) = r(A, \varphi, Z) - Df_m(Z)$, where $r(A, \varphi, Z) = \max_q pq - c(A, \varphi)q$. A firm will import whenever the net profit from importing is greater than the net profit achieved using domestic materials alone, $\pi(A(X, 1), \varphi, Z, 1) - \pi(A(X, 0), \varphi, Z, 0) \geq 0$.

To obtain an empirical specification for the import decision, define the latent variable, D^*, as $D^* = \pi(A(X, 1), \varphi, Z, 1) - \pi(A(X, 0), \varphi, Z, 0) = \mu_D(Z) - V$, 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 $V = [\pi(A(X, 1), \varphi, Z, 1) -$

[6] The latter is an extreme assumption but a similar argument goes through when the impact of importing on the skill-biased technology A term is sufficiently large relative to its impact on the Hicks neutral technology level φ.

$\pi(A(X,0),\varphi,Z,0)] - \mu_D(Z)$ is a mean-zero unobserved stochastic component. Then, we have a latent variable model of importing:

$$D^* = \mu_D(Z) - V, \qquad D = 1 \quad \text{if } D^* \geq 0, \; D = 0 \quad \text{otherwise.} \tag{6}$$

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

The random variable V captures both the idiosyncratic productivity shock φ and the random components in the skill-biased technology level, ϵ and U. Since $\pi(A(X,1),\varphi,Z,1) - \pi(A(X,0),\varphi,Z,0)$ is strictly increasing in the value of ϵ, the random variables V and ϵ are negatively correlated when ϵ is independent of φ and U. This implies that a plant with high value of ϵ—a plant which expects large productivity gains from importing—is more likely to self-select into importing.

3.2 The Marginal Treatment Effect

To evaluate the heterogeneous impact of importing on the demand for skill, we also use the framework developed by Heckman and Vytlacil (1999, 2005, 2007a, 2007b). Define S_1 as the log of potential demand for skilled labor relative to unskilled labor if the plant chooses to import and, likewise, let S_0 be the log of potential skill demand if the plant chooses not to import. The relative demand for skilled labor can then be written as

$$S_1 = \mu_1(X) + U_1 \text{ and } S_0 = \mu_0(X) + U_0, \tag{7}$$

where, allowing for the average value of β to depend on X in (5), $\mu_1(X) \equiv E[S_1|X] = \bar{\beta}(X) + X\gamma'$ and $\mu_0(X) \equiv E[S_1|X] = X\gamma'$ while $U_1 = \epsilon + U$ and $U_0 = U$. The impact of importing on the demand for skilled workers depends on the plant-specific ability to adopt foreign technology embedded in imports since $S_1 - S_0 = \bar{\beta}(X) + U_1 - U_0$.

Now reconsider our simple latent variable model (6) for the decision to import. 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 section 3.1, we expect that a plant with a larger value of $U_1 - U_0 = \epsilon$ will gain more from importing due to greater returns from foreign technology, and hence the value of V is low. In other words, $E[U_1 - U_0|V]$ is decreasing in V. Let $P(Z)$ denote the probability of importing conditional on Z so that $P(Z) = \text{Prob}(\mu_D(Z) > V) = F_V(\mu_D(Z))$. If we define a uniform random variable $U_D \equiv F_V(V)$, the import decision (6) is alternatively written as $D = 1$ if $P(Z) \geq U_D$ and $D = 0$ otherwise. Note that since $E[U_1 - U_0|V]$ is strictly decreasing in V, so is $E[U_1 - U_0|U_D]$ in U_D. Then, we define the marginal treatment effect (MTE) as

$$\Delta^{MTE}(x,p) = E[S_1 - S_0|X = x, U_D = p] = E[\bar{\beta}(X) + U_1 - U_0|X = x, U_D = p]. \tag{8}$$

This is the mean treatment effect for plants with $X = x$ and $P(Z) = p$ when $U_D = p$. That is, it is the mean impact from importing on the demand for skilled labor among plants with $X = x$ and $P(Z) = p$ when the realization of the unobserved random variable U_D is such that the plant is just indifferent between importing and not importing.

A key advantage of the MTE is that it allows us to compute all the conventional treatment parameters, such as the ATE, the TT, and the TUT, as weighted averages of the MTE, each computed with a different weighting function (see Heckman and Vytlacil (2005, 2007a, 2007b)). We estimate the MTE and treatment parameters following a procedure similar to that of Carneiro, Heckman, and Vytlacil (2011). Because the support of P for each value of X is small, as in Carneiro, Heckman, and Vytlacil (2011), we assume that (X, Z) is independent of (U_1, U_0, U_D). Then, the MTE can be identified within the support of $P(Z)$ as $\Delta^{MTE}(x, p) = \bar{\beta}(x) + E[U_1 - U_0|U_D = p]$, where the term $\bar{\beta}(x)$ represents the average treatment effect when $X = x$ while $E[U_1 - U_0|U_D = p]$ represents the component of the MTE that depends on U_D. Because X is a high-dimensional vector, allowing the value of $\bar{\beta}$ to depend on all variables in X leads to imprecise estimates of $\bar{\beta}(X)$. We set $\bar{\beta}(X) = \tilde{X}'\theta$, where $\tilde{X}$ contains the log of each skill ratio in 1996, $\log(L_s^j/L_u^j)_{1996}$, and includes dummies for plants that did not hire any skilled or unskilled workers, $d_s^j = 1(L_s^j = 0)$ and $d_u^j = 1(L_u^j = 0)$ in 1996.[7] Then,

$$E[S|X = x, P(Z) = p] = x'\gamma + p\tilde{x}'\delta + K(p), \quad \Delta^{MTE}(x, p) = \tilde{x}'\delta + K'(p), \tag{9}$$

where $K(p) = E[U_1 - U_0|U_D \leq p]p$ and $K'(p)$ is the first derivative of $K(p)$. We estimate γ, δ, and $K(p)$ by a partially linear regression of S on X and $P(Z)$ (Robinson, 1988) with local polynomial regressions as described in Appendix B.

4 Empirical Results

4.1 Definitions of Variables and Sample Selection

All outcome variables and most explanatory variables are measured in 2006. The lagged value of outcome variables are also included in the set of explanatory variables so that our sample consist of plants that are present in both the 1996 and 2006 data sets. The definitions of variables and their descriptive statistics are reported in Appendix D.

We consider five different outcome variables for S. Our first two measures, $\ln(L_s^p/L_u^p)_{06}$ and $\ln(L_s^n/L_u^n)_{06}$, directly capture the number of skilled workers within each occupation category where L_s^j and L_u^j are the number of skilled workers and unskilled workers, respectively, employed in occupation $j \in \{p, n\}$, the subscripts "p" and "n" distinguish production and non-production

[7] When we estimated (9) by setting $\tilde{X}$ equal to all variables in X except for the local wage ratio, industry dummies, and province dummies, we found that the interaction term between the propensity score and the lagged value of the outcome variable in 1996 were estimated significantly across different samples while the interaction terms with other variables in X were insignificant.

workers, respectively, and the subscript "06" indicates that a variable is measured in 2006. As before, we define a skilled worker as one with at least a high school degree. The next two outcome variables, $(W_s L_s^p/(W_s L_s^p + W_u L_u^p))_{06}$ and $(W_s L_s^n/(W_s L_s^n + W_u L_u^n))_{06}$, measure the ratio of skilled workers' wages to the total wage bill in each occupation category, where W_s and W_u represent local market wages for skilled workers and unskilled workers, respectively. A non-trivial number of plants do not hire any skilled workers in each occupation. When the log of the ratio of skilled workers to unskilled workers is used as an outcome variable, we simply ignore these plants for which we cannot compute the outcome variable. However, this omission itself may generate selection bias. Therefore, we consider the skilled worker's wage share in the total wage bill for occupation j, $W_s L_s^j/(W_s L_s^j + W_u L_u^j)$, as an alternative outcome variable, which is related to changes in the skill-biased technology parameter, $A/(1+A)$, when we take the limit of $\sigma \to 1$ in production function (1). We also consider the ratio of non-production workers to production workers, $\ln((L_s^n + L_u^n)/(L_s^p + L_u^p))_{06}$, which is often used as a measure of skill intensity in the existing literature.

To control for the initial level of skilled biased technology in 1996, X includes the lagged value of the outcome variable in 1996, denoted by using the subscript "96" in place of "06," and dummy variables for plants that did not hire any skilled or unskilled workers in each occupation in 1996, denoted by $d_{s,96}^j$ and $d_{u,96}^j$ for $j = p, n$. Here, we assume that the lagged outcome variable, say, $\ln(L_s^p/L_u^p)_{96}$ takes a value equal to zero when either $L_s^p = 0$ or $L_u^p = 0$. We also include capital stock in X to control for possible capital-skill complementarity. In addition, X contains the plant's current export status, our estimate of Hicks-neutral productivity φ, the local skilled-unskilled wage ratio,[8] a large set of dummy variables to capture differences across foreign ownership, R&D expenditures, worker training expenditures, industries and provinces. Using an extended version of production function (1), we estimate a model consistent measure of Hicks-neutral productivity φ based on the frameworks developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2006) and Gandhi, Navarro and Rivers (2013) as described in Appendix C. For robustness, we also estimated a conventional measure of TFP from a standard Cobb-Douglas production function and used this in place of our Hicks-neutral productivity measure. Finally, $Z \backslash X$ includes our instruments.

4.2 IV Results

4.2.1 Production Workers and Non-Production Workers

Table 2 presents the results from estimating equation (4) by OLS and IV when we use the log of the ratio of skilled production to unskilled production workers as its dependent variable. Columns (1)-(4) report the results for the full sample while columns (5)-(8) report those for the

[8] The wage ratio is measured through a series of Mincer regressions described in Appendix A. We proceed in this fashion so to isolate the local difference in wages due to education alone, rather than have differences reflect differences in demographics, experience, etc across regions.

sample of initial non-importers. Using only the sample of plants that were not importing in 1996 allows us to consider the impact of transport costs on plants who made their location decision before they began using imported materials.

As reported in columns (1) and (5), the OLS point estimate suggests that importing significantly increases the relative demand for skilled workers within the production occupation by 25 log basis points. Columns (2)-(4) and (6)-(8) report the results from IV regressions using different sets of IVs. For columns (2) and (6), we use a single dummy instrumental variable, denoted by d_{TC}, that takes a value equal to 1 if the transport cost is less than its median value; columns (3) and (7) use our continuous measure of transport cost as an instrument while columns (4) and (8) use transport cost, the change in output tariffs, the change in input tariffs, and interactions between transport cost and tariff measures as instruments. The first stage regression indicates that transportation costs are always a strong predictor of import behavior while output tariffs are good predictors of export behavior. See Table D.3 in Appendix D.

Across different sets of IVs and different samples, our IV estimates are larger than the OLS estimate by an order of magnitude; for the full sample, the point estimates on importing range between 2.49-2.61 indicating that importing increases the relative demand for skilled workers within the production occupation by over 200 percent. In a "standard" case where we assume that there is no heterogeneity in β in (4), the finding that the IV estimate is much larger than the OLS estimate could be viewed as puzzling since the OLS bias may likely be upward in this case. When the coefficient β is random, however, the finding of the large IV estimate is less puzzling because the IV estimator identifies the local average treatment effect.

In columns (2) and (6), we may interpret our IV estimate as the estimated average value of β among plants induced change their import choice when we counterfactually change their values of the discrete instrumental variable d_{TC}. Our results suggest that, on average, only those plants with very high values of β—interpreted as plants with a better ability to adopt skill biased technology—choose to change their import status in response to the change in transport cost. When we use continuous instrumental variables in columns (3)-(4) and (7)-(8), we find similar IV estimates to those from using d_{TC} as an instrument alone.

The control variables in Table 2 generally report consistent and intuitive coefficients. The estimated coefficients on plant-level export status are often negative, which reflects the fact that Indonesia has a comparative advantage in unskilled-labor intensive goods. The significant positive capital and training coefficients indicate both capital and training are complementary to hiring skilled labor. On the other hand, foreign ownership is often negatively associated with the demand for skilled labor, suggesting that foreign ownership is a substitute for skill-intensive production processes (e.g. by offshoring the skill-intensive portion of production abroad). The estimated coefficient on Hicks-neutral productivity φ is negative, which suggests a trade-off between the adoption of skill-biased technology and the adoption of technology that is unbiased across skill differences. The estimated coefficient on the lagged value of the outcome variable is positive and significant, reflecting either the persistence of unobserved characteristics that affect the plant's demand for skills or the presence of adjustment costs associated with changing the plant's skill ratio. The coefficient on relative wages is negative, as expected, but insignificant.

Table 3 reports a number of robustness checks for the IV results using the sample of initial non-importers. First, ignoring the endogeneity of the plant's export decision may lead to the bias in the estimated coefficient on import status given the evidence that importing and exporting are closely related activities (see Kasahara and Lapham, 2013). To examine this issue, we estimate the skill equation using the subsample of plants that do not export either in 1996 or 2006, as well as by instrumenting both import and export status using the subsample of plants that did not export in 1996; we find that the point estimates for importing remain significantly positive in all cases as reported in columns (1)-(4) of Table 3. Second, across different sets of IVs, we continue to find a significant and positive effect of importing when we use conventional TFP in place of our estimated Hicks-neutral productivity as reported in columns (5) and (6).[9] Third, we use the skilled labor share of the production wage bill, $\frac{W_s L_s^p}{W_s L_s^p + W_u L_u^p}$, in place of the log skill ratio as our outcome variable and find that importing is predicted to have a large, positive and significant impact on the relative demand for skilled production workers in most cases as reported in columns (7)-(13) of Table 3.

To examine the effect of importing on the relative skill demand among *non-production* workers, we have repeated the same set of exercises as in Tables 2-3 using the variables defined in terms of non-production workers in place of those defined in terms of production workers. Table 4 reports the summary of results. In columns (3)-(4) of Panel A in Table 4, importing appears to have a large significant impact on demand for skilled non-production workers when we study the sample which includes both 1996 importing and non-importing plants. However, when we examine the sample of initial non-importers the result is sensitive to the choice of IVs and outcome variables as well as conditioning on export status; in Panel B of Table 4, where we examine the robustness of the results, we find no evidence for the positive effect of importing on the relative skill demand among non-production workers. Table 5 reports the results when we use the log of the ratio of non-production to production workers in place of the log of the ratio of skilled workers to unskilled workers within each occupation category. In this case the dependent variable no longer accounts for any (within-occupation) education differences. Across different samples and instrument sets, no significant relationship between importing and the demand for skilled labor is ever found. We highlight this feature of our results because it is strongly indicative of the importance of using an education-based measure of skill when considering the

[9]Hicks-neutral productivity is estimated to take a negative coefficient in Table 2, while our naively estimated TFP takes the opposite sign in column (1) of Table 3. While these results may seem contradictory, they are in fact exactly what we should expect in this instance. By ignoring the skill-biased component of productivity, the conventional TFP measure confuses both the skill-biased and Hicks-neutral components and, as a result, is likely to be positively correlated with the demand for skilled labour. In contrast, the Hicks-neutral productivity term we estimate disentangles these two components of productivity. Plants with larger values of skill-biased productivity will naturally be more likely to have smaller measured Hicks-neutral productivity, *ceteris paribus*.

impact of trade on the demand for skilled labor.

4.2.2 Discussion

Although we have presented evidence that importing leads to an increase in the demand for skill among production workers, the mechanism behind this result has been largely uninvestigated thus far. As we discussed, one plausible mechanism is that importing induces the adoption of skill-biased technology. While there is no direct data on foreign technology adoption, our data set includes a variable which captures whether a plant adopts a standardized production process, such as those recognized by the International Organization for Standardization (ISO) or the International Electrotechnical Commission (IEC).[10] The use of standards may allow Indonesian plants to have better communication with foreign suppliers, facilitating the adoption of foreign skill-biased technology.

In columns (1)-(4) of Table 6, we estimate the effect of standards on the skill ratio among production workers with the sub-sample of initial non-importers using the same specifications as in columns (1)-(4) of Table 3, respectively, but replacing the import dummy with a dummy for standardization, where we control for the history of export status since standardization is likely to be closely associated with exporting activities.[11] The results in columns (1)-(4) indicate that the adoption of standards significantly increases the demand for skilled production workers. We also estimate a linear probability model for standardization while instrumenting import (and export) decisions using IVs in columns (5)-(7) of Table 6 and find that importing significantly increases the probability of the adoption of standards. These findings reflect that importing is likely associated with the adoption of technology and that the adoption of technology in turn leads to an increase in the demand for skilled labor.

Feenstra and Hanson (1996, 1997) present a model with a continuum of goods that highlights another mechanism through which trade liberalization possibly increases the demand for skilled labor in developing countries. In the model, the most skill-intensive goods in developing countries correspond to the least skill-intensive goods in developed countries, and trade liberalization induces the most skill-intensive goods in developing countries to be exported to developed countries, leading to an increase in the demand for skilled labor in developing countries.

We examine the following two hypotheses that are broadly consistent with the implications of Feenstra and Hanson's model. The first hypothesis is that a plant that starts exporting after

[10]Specifically, the survey question asks "Does this establishment use standard of production process?" with the following list of standards: ISO (International Organisation for Standardization), IEC (International Electrotechnical Commission), ITU (International Telecommunication Union), CAC (Codex Alimentarius Commission), AFNOR (Association Francaise de Normalisation), ANSI (American National Standard Institute), BIS (Bureau of India Standard), BSI (British Standards Insitution), DIN (Deutshes Institute for Nonnung ev), JISC (Japanese Industrial Standartds Commitee), SAL (Standards Australia), SNI (Standar Nasional Indonesia), ASTM (American Society for Testing and Material), ASME (American Standard of Mechanical Engineering), and NFPA (National Fire Protection Association). Unfortunately, no further information on which standards are used is available.

[11]The transport cost is a strong predictor of the use of standards. See Table D.3 in Appendix D.

trade liberalization must produce skill-intensive goods so that their demand for skilled labor is higher than other plants. The second hypothesis is that the higher the initial level of skills, the more likely it is that the plant starts exporting after trade liberalization. Table 7 shows that neither of these hypotheses appear to hold in our Indonesian plant-level data. Columns (1)-(2) of Table 7 report the estimated effect of exporting on the skill ratio among production workers using the sample of initial non-exporters that do not import in 1996 or 2006 when we instrument exporting, while column (3) reports the same estimate when we instrument both importing and exporting using the sample of plants that do not export or import in 1996, but possibly do so in 2006. We find no evidence that plants that start exporting between 1996 and 2006 increase the demand for skilled production workers conditional on the history of import status. Further, by regressing an export dummy in 2006 on the log of skill ratio among production workers in 1996, columns (4)-(6) of Table 7 show that the initial level of skill intensity among production workers does not have any predictive power for export status in 2006. These results indicate that the mechanisms suggested by Feenstra and Hanson model do not appear relevant for explaining the observed skill upgrading in Indonesia.

4.3 The Demand for Skill: Marginal Treatment Effects

4.3.1 Propensity Scores and the Skill Demand Equation (9)

For brevity, we focus on the estimates of import decisions and the skill demand equation (9) for the sample of production workers. We estimate the import probabilities for each plant using a logit specification where we include the interaction terms between the lagged value of the outcome variable in 1996 and instruments as additional explanatory variables. Table 8 reports the estimate of the coefficient and marginal derivative for each variable with bootstrapped standard errors for the full sample and the sample of initial non-importers.[12] We find that transport costs are always a strong predictor of importing. Furthermore, we find that productive and capital-intensive plants, foreign-owned plants, research-active plants, exporters and plants that are training employees in the current period are more likely to import.

Figure 1 plots the distribution of estimated propensity scores for importing and non-importing plants in both the full sample and the subsample of initial non-importers. It is evident that the common support of the propensity scores across importing and non-importing plants does not span the full unit interval. For this reason, we restrict our computation of treatment effects to the region where there is significant overlap between the propensity scores of non-importing and importing plants as reported in the second to the last row of Table 10; specifically, treatment effects are computed over the region with the minimum and maximum values given by the 1^{st}

[12] The sample excludes plants that belong to a 3-digit ISIC industry or province within which there is no variation in import status because, in such cases, the estimated coefficient of the corresponding industry or province dummy in the logit model would be either infinity or minus infinity.

percentile and the 99^{th} percentile values of estimated propensity scores for which we have common support, respectively. Because there are very few non-importing plants with propensity scores beyond the upper bound of this range, it is difficult to apply nonparametric methods and confidently estimate the MTE outside of this range.

Table 9 reports the estimates of the parameter γ and δ in the skill demand equation (9) using the sample of plants for which the outcome variable is measurable and for which the estimated propensity scores are on the estimated common support. Notably, the coefficient of the interaction term between the lagged value of the log of the skill ratio and the propensity score is negative and significant. Because various treatment effects can be written as the weighted averages of the MTE, this implies that plants with higher initial skill ratios tend to find that importing has a lower impact on their demand for skilled production workers. One possible interpretation is that plants with high initial skill ratios may have already adopted relatively skill-biased technology and, as a result, further adoption of foreign technology induced by importing may not substantially increase their demand for skilled workers. The estimates of the other explanatory variables are largely similar to those of the IV regressions reported in Table 2.

4.3.2 Treatment Effects for Production and Non-production Workers

Figure 2 plots the relationships between the MTE for production workers or non-production workers and U_D along with 90 percent (equal-tailed) bootstrap confidence bands, where the import decision model is estimated for each bootstrap sample so that the first stage estimation error is taken into account. As shown in Figure 2(a)(b), the estimated MTE curve for production workers is well above zero for small values of U_D and is downward sloping in both the full sample and the sample of initial non-importers. These findings indicate that among plants with a high incentive to import due to unobserved characteristics (i.e., a high value of U_D), importing has a greater impact on the demand for skilled production workers (i.e., a higher value of $\epsilon = U_1 - U_0$) than those with low values of U_D. In contrast, when we restrict the sample to initial non-importers in Figure 2(d), the estimated MTE curve for non-production workers is not significantly different from zero across all values of U_D. That is, our findings do not indicate any statistically significant impact of importing on skill upgrading within non-production workers.

Table 10 reports the estimates of various summary measures of the impact of importing on skill demand: the ATE, the TT, the TUT, and policy relevant treatment effects (the MPRTEs and the PRTE), where these treatment effects are computed as the weighted averages of the MTE with weights that integrate to one in the restricted support reported in the second to last row of Table 10. Appendix B discusses the details of our estimation procedure while Appendix D reports the estimated weights for computing different treatment parameters.

The first four columns of Table 10 report the estimated treatment effects for production workers using the log of the production skill ratio or the wage share of skilled workers among production workers as outcome variables. Bootstrap standard errors and the 90 percent equal-tailed bootstrap confidence interval are reported in square brackets and in parentheses, respectively. The ATE, the TT, and the TUT for production workers are estimated to be positive and statistically significant, indicating that importing increases the demand for educated workers within production workers across different groups of plants. Furthermore, the TT is estimated to be substantially larger than the ATE which, in turn, is substantially larger than the TUT. This suggests that there might be substantial unobserved heterogeneity in the effect of importing on skill demand across plants. While plants that were induced to import witnessed large increases in the demand for skilled production workers, the impact of importing on the demand for skilled production workers is substantially smaller for plants that chose not to import.

In contrast, as the last four columns of Table 10 show, the estimated treatment effects for non-production workers vary substantially across samples and measures of skill demand. Given the potential concern with using transport costs as our instrument in the full sample, the results from the subsample of initial non-importers reported in columns (6) and (8) may be preferable; these results consistently indicate that the ATE, the TT, and the TUT are not significantly different from zero.

Table 11 examines the robustness of our results using different samples, specifications, and estimation methods, where we focus on the log of the skill ratio for production workers as the outcome variable and always use the sample of initial non-importers. In column (1), we estimate the treatment effects using the subsample of plants that did not export in both 1996 and 2006 to control for the history of export status, where, according to the bootstrapped confidence intervals, the ATE, the TT, and the TUT are significantly positive at the 10 percent value. Column (2) reports the estimates of treatment effects when we use conventional TFP in place of our estimated Hicks-neutral productivity. In this case, the treatment effects are smaller than the baseline case and insignificant for the ATE and the TUT. Because the conventional TFP measure is likely to be positively correlated with skill-biased productivity, the use of TFP in place of Hicks-neutral productivity could have lead to a downward bias in the estimated treatment effects.

In column (3) of Table 11, we estimate the partial linear model (9) where we use a sieve estimator based on the 4th order polynomials in $P(Z)$ instead of the local polynomial estimator as discussed in Appendix B. Column (4) considers a specification of the skill demand equation (9) with no interactions with Z so that $\tilde{X}$ is empty while column (5) estimates treatment effects over the estimated common support instead of the subset of common support defined by the 1^{st} percentile and the 99^{th} percentile of observations that are on the common support.[13] The estimates of the ATE, the TT, and the TUT in columns (3)-(5) of Table 11 are significantly

[13]To estimate the treatment effects reported in Table 11, we use the same specification for the decision to import as the specification reported in Table 8 except that, in column (4), we exclude the interaction terms between instruments and the 1996 value of the log of skill ratio from the set of explanatory variables.

positive and exhibit the patterns similar to those reported in column (2) of Table 10.

4.3.3 Policy Experiment

Our IV and MTE estimates confirm that importing has a substantial impact on the demand for skilled production workers. Nonetheless, it is less clear how large the effect of *further* changes in policy related variables would be on the demand for skilled production workers. To examine this issue, we consider alternative policies that change the probability of importing but do not affect potential outcomes or the unobservables related to import decisions, (S_0, S_1, V) defined in (6)-(7), and compute the mean effect of going from a baseline policy to an alternative policy per plant shifted into importing. This treatment effect is called the Policy Relevant Treatment Effect (PRTE) proposed by Heckman and Vytlacil (2005, 2007b). Let $P^*(Z)$ and $P(Z)$ denote the propensity scores under an alternative policy and a baseline policy, respectively.

We consider the alternative policy of reducing the cost of shipping goods to the nearest port by 1 percent so that $P^*(Z)$ is set to the propensity score under the alternative transport cost of $TC^* = 0.99TC$. The PRTE under this alternative policy captures the causal impact that a marginal improvement in roads and infrastructure would have on the relative demand for skilled workers across plants. Note that this policy change will have a heterogeneous impact across plants. We compute the estimate of what the PRTE would be when we restrict the support of the propensity scores to the restricted support reported in the second to the last row of Table 10.[14] We also compute the marginal version of PRTE called the Marginal Policy Relevant Treatment Effect (MPRTE) proposed by Carneiro, Heckman, and Vytlacil (2010). Given a sequence of alternative policies indexed by a scalar variable α such that $\lim_{\alpha \to 0} P^*_\alpha(Z) = P(Z)$, the MPRTE is defined as the limit of a sequence of PRTEs as α approaches to zero. We consider two policy sequences as described in Carneiro, Heckman, and Vytlacil (2010): (i) a policy that increases the probability of importing by α so that $P^*_\alpha = P + \alpha$ and (ii) a policy that shifts one of the components in Z, say Z^k, so that $Z^k_\alpha = Z^k + \alpha$.

As reported in columns (1)-(4) of the lower panel of Tables 10, the estimates of the MPRTEs and the PRTE for production workers indicate that the subset of plants that would be induced to start importing by further policy change would substantially increase their demand for skilled production workers. These estimates are not sensitive to changes in specifications, samples, and estimation methods on the whole as shown in the lower panel of Table 11. In contrast, for non-production workers, the results of the PRTE and the MPRTEs are mixed at best as reported in columns (5)-(8) of Tables 10.

[14] As discussed in Carneiro, Heckman, and Vytlacil (2010), the PRTE is not identifiable without strong support conditions. To compute the estimate of what PRTE would be on the restricted support, we replace the value of the propensity scores with the maximum value of the support whenever the value of the propensity scores under the alternative policy is larger than the maximum value of the restricted support so that all of the propensity scores under the alternative policy lies on the restricted support.

4.3.4 Discussion

Consistent with our IV results, we find strong evidence that importing has a large and significant impact on the relative demand for skilled production workers, but little evidence that importing affects the demand for skill among non-production workers. To examine whether skill demand is related to the adoption of technology, we also estimated the treatment effects of adopting standard production processes, where we replace the import dummy with a dummy for the adoption of standards while using the sample of initial non-importers which did not export in 1996 or 2006. As reported in column (6) of Table 11, the TT is estimated to be substantially larger than the ATE or the TUT while the estimates for the PRTE and the MPRTEs indicate that further policy change which promotes the adoption of standards would have a substantial impact on the demand for skilled production workers.

Last, we again check if we would have made broadly different conclusions if we had only used production and non-production data without education level data as typically done in prior research. Using the log of the ratio of non-production workers to production workers as the outcome variable with the sample of initial non-importers, we find no effect of importing on the relative demand for non-production workers; the ATE, the TT, the TUT, the PRTE, and the MPRTEs are not significantly different from zero while the estimated MTE curve is nearly flat and the confidence band is wide and includes zero. See Table D.6 and Figure D.2 in Appendix D. Our findings indicate that while importing does have a large, economically important and statistically significant impact on the demand for skilled production workers, it is possible, even likely, that without sufficiently disaggregated data we may misleadingly conclude that importing has little impact on plant-level skill-demand.

5 Conclusion

This paper studies the impact that importing foreign materials has on the demand for educated workers among Indonesian manufacturing plants. We develop a model of heterogeneous manufacturing plants where the decision to import may be influenced by the return from importing through the adoption of skill-biased technology, where the degree to which importing induces skill-biased technological change is potentially heterogenous across plants and unobservable to the researcher. To the extent that importing affects skill-biased productivity we would expect that it will directly impact mix of skilled and unskilled workers hired by Indonesian manufacturers.

To estimate the impact of importing on the demand for skilled workers we exploit detailed data from the Indonesian manufacturing survey. Our data documents the education level of every worker in every manufacturing plant with at least 20 employees. Defining a skilled worker as one with a high school education we find that importing greatly increases the demand for skilled production workers among Indonesian importers. In contrast, importing is rarely found to have a significant impact on the relative demand for skilled non-production workers. We also document significant evidence that the impact of importing on the demand for skilled production workers is heterogeneous across plants. In particular, plants which were induced to import during our sample period were estimated to be those with generally high returns from importing.

We further find that policies that improve transportation infrastructure in Indonesia would encourage new plants to start importing and increase the demand for skilled production workers among those new importers. Notably, however, when we repeat any of our experiments using a conventional measure of relative skill demand, defined as the ratio of non-production to production workers, we do not find any impact of importing on the demand for skilled labor.

References

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer (2006) "Structural Identification of Production Functions", Department of Economics UCLA.

Amiti, Mary, and Donald Davis (2012) "Trade, Firms, and Wages: Theory and Evidence," *Review of Economic Studies*, 79(1): 1-36.

Amiti, Mary, and Lisa Cameron (2012) "Trade Liberalization and the Wage Skill Premium: Evidence from Indonesia," *Journal of International Economics*, 62(2): 277-287.

Amiti, Mary, and Jozef Konings (2007) "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Reviews*, 97(5):1611-1638.

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. Manfuacturing: 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 (1997) "Exporters, Skill Upgrading, and the Wage Gap," *Journal of International Economics*, 42: 1-25.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding and Peter K. Schott (2007) "Firms in International Trade," *Journal of Economic Perspectives*, 21(3): 105-130.

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.

Bloom, N., M. Draca and J. Von Reenan (2011) "Trade Induced Technical Change: The Impact of Chinese Imports on IT and Innovation," mimeo, Stanford University.

Burstein, Ariel, Javier Cravino and Jonathan Vogel (2013) "Importing Skill-Biased Technological Change," *American Economic Journal: Macroeconomics*, 5(2): 32-71.

Burstein, Ariel and Jonathan Vogel (2012) "International Trade, Technology, and the Skill Premium," mimeo, UCLA.

Bustos, Paula (2011) "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 (2010) "Evaluating Marginal Policy Changes and the Average Effect of Treatment for Individuals at the Margin," *Econometrica* 78(1): 377-394.

Carneiro, P., J.J. Heckman, and E. Vytlacil (2011) "Estimating Marginal Returns to Education," *American Economic Review*, 101: 2754-2781.

Chor, D. (2010) "Unpacking Sources of Comparative Advantage: A Quantitative Approach.," *Journal of International Economics*, 82(2): 152-167.

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.

Cosar, A. Kerem (2011) "Adjusting to Trade Liberalization: Reallocation and Labor Market Policies," mimeo, University of Chicago.

Costinot, Arnaud and Jonathan Vogel (2010) "Matching and Inequality in the World Economy," *Journal of Political Economy*, 118(4): 747-786.

Davis, Donald R. and James Harrigan (2011) "Good Jobs, Bad Jobs, and Trade Liberalization," *Journal of International Economics*, 84(1), 26-36.

De Loecker, Jan (2011) "Product Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity," *Econometrica*, 79(5): 1407-1451.

De Loecker, Jan, Pinelopi Goldberg, Amit Khandelwal and Nina Pavcnik (2012) "Prices, Markups and Trade Reform," mimeo, Princeton University.

Doms, Mark, Timothy Dunne, and Kenneth R. Troske (1997) "Workers, Wages, and Technologies," *Quarterly Journal of Economics*, 112: 253-290.

Doraszelski, Ulrich and Jordi Jaumandreu (2013) "R&D and Productivity: Estimating Production Functions When Productivity is Endogenous," *Review of Economic Studies*, forthcoming.

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.

Egger, H. and U. Kreikemeier (2009) "Firm Heterogeneity and the Labor Market Effects of Trade Liberalization," *International Economic Review*, 50 (1): 187-216.

Fan, J. and T.H. Yim (2004) "A Crossvalidation Method for Estimating Conditional Densities," *Biometrika*, 91: 819-834.

Felbermayr, G., J. Prat, H. Schmerer (2011) "Globalization and labor market outcomes: Wage bargaining, search frictions, and firm heterogeneity," *Journal of Economic Theory*, 146 (1): 39-73.

Feenstra, Robert and Gordon Hanson (1996) "Globalization, Outsourcing, and Wage Inequality," *American Economic Review*, 86(2): 240-245.

Feenstra, Robert and Gordon Hanson (1997) "Foreign Direct Investment and Relative Wages: Evidence from Mexicos Maquiladoras," *Journal of International Economics*, 42(3/4): 371-393.

Feenstra, Robert and Gordon Hanson (1999) "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990," *Quarterly Journal of Economics*, 114 (3): 907-940.

Frazer, Garth (2013) "Imports, Import Sources and Skill Utilization," mimeo, University of Toronto.

Frías, J. A., D. S. Kaplan and E. A. Verhoogen (2009) "Exports and Wage Premia: Evidence from Mexican Employer-Employee Data," mimeo, Columbia University.

Gandhi, Amit, Salvador Navarro and David Rivers (2013) "On the Identification of Production Functions: How Heterogeneous is Productivity," mimeo, University of Wisconsin.

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 (2005): Trade Protection and Wages: Evidence from the Colombian Trade Reforms, *Journal of International Economics,* 66(1): 75-105.

Goldberg, P.K. and N. Pavcnik (2007) "Distributional Effects of Globalization in Developing Countries," *Journal of Economic Literature*, Vol. XLV, pp. 3982

Gonsaga, Gustavo, Naercio Menezes Filho, and Christina Terra (2006) "Trade liberalization and the evolution of skill earnings differentials in Brazil," *Journal of International Economics*, 68: 345-367.

Griliches, Zvi (1969) "Capital-Skill Complementarity," *Review of Economics and Statistics,* 51: 465-468.

Halpern, László, Miklós Koren, and Adam Szeidl (2009) "Imports and Productivity," CEFIG Working paper no. 8. 2009.

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:: 4875-5143.

Helpman, E., O. Itskhoki, and S. Redding (2010) "Inequality and Unemployment in a Global Economy," *Econometrica*, 78(4): 1239-1283.

Hendayana, Sumar, Asep Supriatna and Harun Imansyah (2008) "Indonesia's Issues and Challenges on Quality Improvement of Mathematics and Science Education," Indonesia University of Education, Indonesia.

Imbens, Guido, and Joshua Angrist (1994) "Identification and Estimation of Local Average Treatment Effects," *Econometrica* 62(2): 467-475.

Kam, Ho Wah (2006) "English Language Teaching in East Asia Today: An Overview," *Asia Pacific Journal of Education*, 22(2): 1-22

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.

Kijima, Y. "Why did wage inequality increase? Evidence from urban India 1983-99," *Journal of Development Economics*, 81: 97-117.

Koren, M. and M. Csillag (2011) "Machines and machinists: capital-skill complementarity from an international trade perspective," CeFiG Working Papers, No. 13.

Kugler, M. and E. Verhoogen (2009) "Plants and Imported Inputs: New Facts and an Interpretation," *American Economic Review Papers and Proceedings*, 99(2):501-507.

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

Levinsohn, James and Amil Petrin (2003) "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 70:317-341.

Matsuyama, Kiminori (2007) "?Beyond Icebergs: Towards A Theory of Biased Globalization," *Review of Economic Studies*, 74: 237-253.

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

Olley, G. Steven and Ariel Pakes (1996) "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 65(1); 245-276.

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.

Robinson, P. M. (1988) "Root-N-Consistent Semiparametric Regression," *Econometrica*, 56(4): 931-954.

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.

Trefler, Daniel (2004) "The Long and Short of the Canada-U.S. Free Trade Agreement," *American Economic Review*, 94(4): 870-895.

Vannoorenberghe, Gonzague (2011) "Trade between symmetric countries, heterogeneous firms, and the skill premium," *Canadian Journal of Economics*, 44(1):148-170.

Verhoogen, Eric (2008) "Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector," *Quarterly Journal of Economics*, 123(2): 489-530.

Wooldridge, Jeffrey (2009) "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables," *Economic Letters*, 104:112-114.

Yeaple, Stephen (2005) "A Simple Model of Firm Heterogeneity, International Trade, and Wages," *Journal of International Economics*, 65(1): 1-20.

Table 1: Importing and Skill Intensity 2006

	Panel A: All Workers									
	Highest Degree Completed/Fraction									
	No Primary	Primary	Jr. High	High	College	Grad. School	Training/Worker	R&D/Worker	Non-Prod./All Workers	No. of Obs.
All Plants										
Importers	0.015	0.071	0.302	0.538	0.073	0.0006	70.9	73.8	0.184	5,512
	(0.075)	(0.171)	(0.218)	(0.237)	(0.093)	(0.004)	(724.4)	(1037.1)	(0.151)	
Non-Importers	0.059	0.275	0.306	0.323	0.036	0.0003	23.2	17.8	0.135	23,952
	(0.151)	(0.302)	(0.248)	(0.295)	(0.078)	(0.005)	(570.0)	(294.4)	(0.163)	
Exporting Plants										
Importers	0.007	0.069	0.222	0.609	0.091	0.0011	150.7	158.2	0.184	1,519
	(0.044)	(0.124)	(0.208)	(0.235)	(0.103)	(0.0065)	(1,310.4)	(1,826.3)	(0.159)	
Non-Importers	0.030	0.190	0.293	0.437	0.050	0.0003	65.0	46.5	0.150	3,690
	(0.102)	(0.239)	(0.227)	(0.292)	(0.075)	(0.0034)	(1,141.0)	(613.4)	(0.160)	
Non-Exporting Plants										
Importers	0.018	0.072	0.333	0.511	0.066	0.0004	40.6	41.6	0.184	3,993
	(0.084)	(0.186)	(0.214)	(0.232)	(0.088)	(0.0031)	(260.8)	(461.2)	(0.148)	
Non-Importers	0.065	0.291	0.309	0.302	0.033	0.0002	15.6	12.6	0.132	20,262
	(0.158)	(0.309)	(0.252)	(0.291)	(0.078)	(0.0056)	(383.0)	(183.9)	(0.163)	
Foreign-Owned Plants										
Importers	0.008	0.070	0.170	0.651	0.099	0.0015	176.4	360.0	0.196	303
	(0.045)	(0.111)	(0.183)	(0.238)	(0.108)	(0.0054)	(744.1)	(3,726.2)	(0.177)	
Non-Importers	0.023	0.130	0.208	0.555	0.083	0.0007	59.9	111.5	0.178	376
	(0.086)	(0.185)	(0.205)	(0.294)	(0.108)	(0.0038)	(337.6)	(843.4)	(0.158)	
Domestic Plants										
Importers	0.037	0.170	0.199	0.513	0.080	0.0012	115.4	100.6	0.179	2,178
	(0.115)	(0.235)	(0.203)	(0.311)	(0.104)	(0.0065)	(1103.6)	(768.8)	(0.170)	
Non-Importers	0.071	0.329	0.276	0.291	0.033	0.0003	26.7	19.3	0.129	19,896
	(0.163)	(0.303)	(0.240)	(0.301)	(0.080)	(0.0058)	(623.5)	(301.2)	(0.164)	

	Panel B: Production vs. Non-Production Workers									
	Production Workers					Non-Production Workers				
	Less than Primary	Primary	Jr. High	High	College Grad.	Less than Primary	Primary	Jr. High	High	College Grad.
All Plants										
Importers	0.016	0.078	0.328	0.544	0.035	0.002	0.018	0.168	0.566	0.245
	(0.077)	(0.182)	(0.234)	(0.264)	(0.071)	(0.037)	(0.092)	(0.204)	(0.236)	(0.232)
Non-Importers	0.061	0.290	0.324	0.309	0.017	0.017	0.085	0.193	0.534	0.172
	(0.156)	(0.314)	(0.267)	(0.315)	(0.065)	(0.107)	(0.232)	(0.288)	(0.352)	(0.257)
Exporting Plants										
Importers	0.008	0.081	0.240	0.627	0.044	0.003	0.024	0.104	0.529	0.340
	(0.046)	(0.144)	(0.225)	(0.266)	(0.084)	(0.026)	(0.086)	(0.157)	(0.254)	(0.271)
Non-Importers	0.030	0.206	0.314	0.429	0.021	0.013	0.053	0.133	0.543	0.258
	(0.104)	(0.256)	(0.247)	(0.320)	(0.060)	(0.091)	(0.166)	(0.223)	(0.322)	(0.292)
Non-Exporting Plants										
Importers	0.018	0.077	0.361	0.513	0.031	0.002	0.016	0.194	0.581	0.207
	(0.086)	(0.195)	(0.229)	(0.256)	(0.066)	(0.040)	(0.094)	(0.215)	(0.227)	(0.203)
Non-Importers	0.067	0.305	0.326	0.287	0.016	0.018	0.091	0.206	0.532	0.154
	(0.163)	(0.322)	(0.270)	(0.309)	(0.066)	(0.110)	(0.244)	(0.298)	(0.358)	(0.245)
Foreign-Owned Plants										
Importers	0.009	0.084	0.181	0.686	0.041	0.004	0.023	0.074	0.498	0.401
	(0.044)	(0.134)	(0.200)	(0.269)	(0.085)	(0.039)	(0.075)	(0.136)	(0.276)	(0.299)
Non-Importers	0.023	0.145	0.229	0.564	0.038	0.012	0.034	0.102	0.506	0.346
	(0.085)	(0.208)	(0.227)	(0.336)	(0.100)	(0.081)	(0.116)	(0.198)	(0.334)	(0.330)
Domestic Plants										
Importers	0.038	0.185	0.216	0.521	0.039	0.006	0.048	0.099	0.539	0.308
	(0.118)	(0.248)	(0.225)	(0.343)	(0.086)	(0.060)	(0.146)	(0.194)	(0.296)	(0.281)
Non-Importers	0.073	0.346	0.290	0.275	0.016	0.021	0.107	0.168	0.529	0.175
	(0.168)	(0.315)	(0.260)	(0.320)	(0.068)	(0.120)	(0.257)	(0.287)	(0.376)	(0.273)

Notes: Standard deviations are in parentheses. The first column indicates current import status, where "importers" denotes plants that import and "non-importers" captures plants that do not import in the current year. The first panel pools all plants in all years. The second and third panel split the sample by export status, while the fourth and fifth panels split the sample by the country of ownership. Specifically, foreign-owned plants are defined as those plants where at least 10% of equity is held by foreign investors while domestic plants are defined as plants for which at least 90% of equity is held by domestic investors.

Table 2: Skill Demand Equation for Production Workers

	Dependent Variable: $\ln(L_s^p/L_u^p)_{06}$							
	Full Sample				Sample of Initial Non-importers ($D_{96}=0$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV Import using d_{TC}	IV Import using TC	IV Import using $(TC, \Delta\tau_m, \Delta\tau_y)$	OLS	IV Import using d_{TC}	IV Import using TC	IV Import using $(TC, \Delta\tau_m, \Delta\tau_y)$
Import	0.2507***	2.6080***	2.4904***	2.5965***	0.2515***	4.2318***	4.3037***	4.2509**
	[0.057]	[0.670]	[0.589]	[0.649]	[0.096]	[1.594]	[1.634]	[1.807]
Export	0.0140	-0.3696***	-0.3545***	-0.3501***	-0.0330	-0.3235**	-0.3194**	-0.2923*
	[0.055]	[0.127]	[0.115]	[0.133]	[0.069]	[0.144]	[0.145]	[0.166]
Capital	0.1379***	0.0871***	0.0889***	0.0980***	0.1457***	0.1098***	0.1081***	0.1178***
	[0.013]	[0.020]	[0.019]	[0.021]	[0.016]	[0.025]	[0.025]	[0.027]
Hicks-neutral φ	-0.2737***	-0.3445***	-0.3445***	-0.3634***	-0.2804***	-0.3389***	-0.3391***	-0.3491***
	[0.038]	[0.049]	[0.048]	[0.053]	[0.044]	[0.058]	[0.059]	[0.065]
Foreign	0.1548	-0.2918	-0.2682	-0.3976**	0.2347	-0.2351	-0.2308	-0.4088
	[0.100]	[0.181]	[0.171]	[0.186]	[0.146]	[0.301]	[0.302]	[0.314]
R&D	0.0511	-0.1199	-0.1068	-0.0778	0.0654	-0.2427	-0.2331	-0.1372
	[0.074]	[0.103]	[0.098]	[0.104]	[0.099]	[0.183]	[0.177]	[0.171]
Training	0.2183***	0.1251**	0.1294**	0.1061	0.2000***	0.0880	0.0821	0.0621
	[0.048]	[0.062]	[0.061]	[0.066]	[0.055]	[0.082]	[0.085]	[0.090]
$\ln(\frac{W_s}{W_u})$	-0.0953	-0.0442	-0.0521	0.0059	-0.0782	-0.0298	-0.0445	-0.0065
	[0.072]	[0.086]	[0.086]	[0.092]	[0.080]	[0.098]	[0.099]	[0.103]
$\ln(\frac{L_s^p}{L_u^p})_{96}$	0.3864***	0.3570***	0.3595***	0.3514***	0.3775***	0.3472***	0.3471***	0.3511***
	[0.017]	[0.022]	[0.022]	[0.024]	[0.021]	[0.028]	[0.029]	[0.031]
$d_{u,96}^p$	0.5642***	0.4077**	0.3895**	0.4133**	0.2906	0.0157	-0.0366	0.0228
	[0.143]	[0.178]	[0.175]	[0.201]	[0.177]	[0.269]	[0.273]	[0.302]
$d_{s,96}^p$	-1.0549***	-0.9872***	-1.0115***	-0.9964***	-1.0593***	-1.1046***	-1.1192***	-1.1314***
	[0.060]	[0.071]	[0.070]	[0.074]	[0.066]	[0.082]	[0.082]	[0.092]
No. Obs.	4,970	4,970	4,914	4,301	3,767	3,767	3,718	3,281
R-squared	0.413	–	–	–	0.379	–	–	–

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included.

Table 3: Robustness Check: Skill Demand Equation for Production Workers using Sample of Initial Non-importers ($D_{96} = 0$)

	Dependent Variable: $\ln(L_s^p/L_u^p)_{06}$					
	(1) Sample of $\text{Export}_{96} = 0$ and $\text{Export}_{06} = 0$; IV Import using d_{TC}	(2) Sample of $\text{Export}_{96} = 0$ and $\text{Export}_{06} = 0$; IV Import using TC	(3) Sample of $\text{Export}_{96} = 0$ and $\text{Export}_{06} = 0$; IV Import using $(TC, \Delta\tau_m, \Delta\tau_y)$	(4) Sample of $\text{Export}_{96} = 0$; IV both Import and Export using $(TC, \Delta\tau_m, \Delta\tau_y)$	(5) Replace φ with TFP; IV Import using TC	(6) Replace φ with TFP; IV Import using $(TC, \Delta\tau_m, \Delta\tau_y)$
Import	3.2080*	4.6053*	5.2353**	5.1904*	4.0235**	3.8712**
	[1.851]	[2.519]	[2.568]	[2.656]	[1.581]	[1.707]
Export				-1.0712	-0.3256**	-0.2904*
				[1.855]	[0.141]	[0.159]
TFP					0.0387	0.0289
					[0.046]	[0.048]
No. Obs.	2,718	2,692	2,412	2,654	3,719	3,282

	Dependent Variable: $\left(\frac{W_s L_s^p}{W_s L_s^p + W_u L_u^p}\right)_{06}$						
	(7) OLS	(8) IV Import using d_{TC}	(9) IV Import using TC	(10) IV Import using $(TC, \Delta\tau_m, \Delta\tau_y)$	(11) Sample of $\text{Export}_{06} = 0$ and $\text{Export}_{96} = 0$ IV Import using $(TC, \Delta\tau_m, \Delta\tau_y)$	(12) Sample of $\text{Export}_{96} = 0$ IV both Import and Export using $(TC, \Delta\tau_m, \Delta\tau_y)$	(13) Replace φ with TFP; IV Import using $(TC, \Delta\tau_m, \Delta\tau_y)$
Import	0.0226	0.8450***	0.7116***	0.5252**	0.7251*	0.4479	0.4977**
	[0.014]	[0.239]	[0.234]	[0.239]	[0.378]	[0.349]	[0.234]
Export	0.0240**	-0.0416*	-0.0280	-0.0111		-0.3696	-0.0107
	[0.012]	[0.024]	[0.023]	[0.024]		[0.368]	[0.024]
TFP							0.0080
							[0.007]
No. Obs.	5,639	5,639	5,576	4,939	3,912	4,207	4,940

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included. Columns (1)-(13) use the same set of explanatory variables as in Table 2 except that we use a "conventional" TFP measure based on a Cobb-Douglas production function in place of Hicks-neutral productivity measure ϕ in columns (5), (6), and (13) while we include $\left(\frac{W_s L_s^p}{W_s L_s^p + W_u L_u^p}\right)_{96}$ in place of $\ln(\frac{L_s^p}{L_u^p})_{96}$, $d_{u,96}^p$, and $d_{s,96}^p$ in columns (7)-(13). The sample of initial non-importers is used in all columns except columns (1)-(3) and (11) which use the subsample of plants that do not export in 2006 or import in 1996 while columns (4) and (12) use the subsample of plants that do not export in 1996 or in 2006 and do not import in 1996.

Table 4: Skill Demand Equation for Non-Production Workers

Panel A: Baseline Specification

	Dependent Variable: $\ln(L_s^n/L_u^n)_{06}$							
	Full Sample				Sample of Initial Non-importers ($D_{96}=0$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV Import using d_{TC}	IV Import using TC	IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	OLS	IV Import using d_{TC}	IV Import using TC	IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$
Import	0.0892	2.3802**	2.3388***	2.6406***	0.2265*	5.2753	3.7538*	3.5420
	[0.074]	[1.079]	[0.797]	[0.884]	[0.124]	[5.038]	[2.241]	[2.337]
Export	0.1877**	-0.1622	-0.1585	-0.2122	0.0384	-0.3624	-0.2432	-0.2360
	[0.073]	[0.186]	[0.152]	[0.168]	[0.093]	[0.431]	[0.221]	[0.218]
No. Obs.	2,254	2,254	2,233	1,923	1,654	1,654	1,635	1,430

Panel B: Robustness Check using Sample of Initial Non-importers ($D_{96}=0$)

	Dependent Variable: $\ln(L_s^n/L_u^n)_{06}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Sample of $\text{Export}_{96}=0$ and $\text{Export}_{06}=0$; IV Import using d_{TC}	Sample of $\text{Export}_{96}=0$ and $\text{Export}_{06}=0$; IV Import using TC	Sample of $\text{Export}_{96}=0$ and $\text{Export}_{06}=0$; IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	Sample of $\text{Export}_{96}=0$; IV both Import and Export using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	Replace φ with TFP; IV Import using TC	Replace φ with TFP; IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$
Import	5.5247	5.3115	0.1457	1.9798	3.5452	3.0180
	[8.034]	[5.089]	[2.847]	[3.298]	[2.184]	[2.201]
Export				-0.9619	-0.2547	-0.2273
				[2.184]	[0.218]	[0.210]
No. Obs.	1,154	1,147	1,027	1,138	1,635	1,430

	Dependent Variable: $\left(\frac{W_s L_s^n}{W_s L_s^n + W_u L_u^n}\right)_{06}$						
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	OLS	IV Import using d_{TC}	IV Import using TC	IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	Sample of $\text{Export}_{06}=0$ and $\text{Export}_{96}=0$ IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	Sample of $\text{Export}_{96}=0$ IV both Import and Export using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	Replace φ with TFP; IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$
Import	-0.0635***	-0.2639	-0.0574	-0.2182	-0.2553	-0.3207	-0.4337
	[0.018]	[0.256]	[0.270]	[0.303]	[0.299]	[0.480]	[0.468]
Export	0.0384**	0.0549**	0.0374	0.0411	0.0414		-0.2212
	[0.015]	[0.026]	[0.026]	[0.031]	[0.031]		[0.507]
No. Obs.	5,639	5,639	5,576	4,939	4,940	3,912	4,207

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in square brackets. Columns (1)-(8) in Panel A use the same set of explanatory variables as in Table 2 except that we use $\ln(\frac{L_s^n}{L_u^n})_{96}$, $d_{u,96}^n$, and $d_{s,96}^n$ in place of $\ln(\frac{L_s^p}{L_u^p})_{96}$, $d_{u,96}^p$, and $d_{s,96}^p$, respectively. Columns (1)-(13) of Panel B use the same set of explanatory variables as those in Panel A except that we use a "conventional" TFP measure based on a Cobb-Douglas production function in place of Hicks-neutral productivity measure ϕ in columns (5) and (6) while we include $\left(\frac{W_s L_s^n}{W_s L_s^n + W_u L_u^n}\right)_{96}$ in place of $\ln(\frac{L_s^n}{L_u^n})_{96}$, $d_{u,96}^n$, and $d_{s,96}^n$ in (7)-(13). The sample of initial non-importers is used in all columns except columns (1)-(3), and (11) of Panel B which use the subsample of plants that do not export in 2006 or import in 1996 while columns (4) and (12) of Panel B use the subsample of plants that do not export in 1996 or in 2006 and do not import in 1996.

Table 5: Skill Demand Equation for the Ratio of Production Workers to Non-Production Workers

	Dependent Variable: $\ln((L_s^p+L_s^n)/(L_s^n+L_u^n))_{06}$							
	Full Sample				Sample of Initial Non-importers ($D_{96}=0$)			
	(1) OLS	(2) IV Import using d_{TC}	(3) IV Import using TC	(4) IV Import using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	(5) OLS	(6) IV Import using d_{TC}	(7) IV Import using TC	(8) IV Import using (TC, $\Delta\tau_m$, $\Delta\tau_y$)
Import	-0.0108	0.4906	0.4031	0.1688	-0.0034	0.4535	0.7170	0.4939
	[0.042]	[0.413]	[0.404]	[0.444]	[0.066]	[0.804]	[0.911]	[1.026]
Export	-0.0260	-0.1128	-0.1126	-0.0581	-0.0213	-0.0595	-0.1013	-0.0725
	[0.047]	[0.087]	[0.086]	[0.099]	[0.057]	[0.090]	[0.097]	[0.113]
No. Obs.	7,123	7,123	7,051	6,192	5,639	5,639	5,576	4,939

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included. Columns (1)-(8) use the same set of explanatory variables as in Table 2 except that we use $\ln((L_s^p+L_s^n)/(L_s^n+L_u^n))_{06}$, $d_{u,96}:=1(L_u^p+L_u^n=0)$, and $d_{s,96}:=1(L_s^p+L_s^n=0)$ in place of $\ln(\frac{L_s^p}{L_u^p})_{96}$, $d^p_{u,96}$, and $d^p_{s,96}$, respectively.

Table 6: Skill Demand, Import Decision, and Adoption of Standards of Production Process using Sample of Plants that Neither Import Nor Export in 1996 (D_{96} =Export$_{96}=0$)

	Dep. Var.: $\ln(L_s^p/L_u^p)_{06}$				Dep. Var.: Dummy for Standards in 2006		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	$D_{96}=0$ Export$_{96}=0$ Export$_{06}=0$	$D_{96}=0$ Export$_{96}=0$ Export$_{06}=0$	$D_{96}=0$ Export$_{96}=0$ Export$_{06}=0$	$D_{96}=0$ Export$_{96}=0$	$D_{96}=0$ Export$_{96}=0$ Export$_{06}=0$	$D_{96}=0$ Export$_{96}=0$ Export$_{06}=0$	$D_{96}=0$ Export$_{96}=0$
IV	IV Standards using d_{TC}	IV Standards using TC	IV Standards using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	IV both Standards and Export using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	IV Import using TC	IV Import using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	IV both Import and Export using (TC, $\Delta\tau_m$, $\Delta\tau_y$)
Standards	1.7283*	2.1351**	3.0635**	3.7553**			
	[0.970]	[1.026]	[1.315]	[1.668]			
Import					1.5642***	1.5051***	1.0713**
					[0.464]	[0.505]	[0.445]
Export				-1.1245			0.5893
				[1.954]			[0.513]
No. Obs.	2,718	2,692	2,412	2,654	4,370	3,912	4,207

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included. Columns (1)-(4) use the same set of explanatory variables, the same IVs, and the same sample as in columns (1)-(4) of Table 3, respectively, except that we replace the import dummy with a dummy for the use of standards. Columns (5)-(7) use the same set of explanatory variables and the same IVs as in columns (2)-(4) of Table 3, respectively, except that the dependent variable is a dummy for the use of standards in place of $\ln(L_s^p/L_u^p)$.

Table 7: Skill Demand, Export Decision, and Initial Skill Levels using Sample of Plants that Neither Import Nor Export in 1996 (D_{96} =Export$_{96} = 0$)

	Dep. Var.: $\ln(L_s^p/L_u^p)_{06}$			Dep. Var.: Export Dummy in 2006		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Export$_{96} = 0$ $D_{96} = 0$ $D_{06} = 0$	Export$_{96} = 0$ $D_{96} = 0$ $D_{06} = 0$	Export$_{96} = 0$ $D_{96} = 0$	Export$_{96} = 0$ $D_{96} = 0$	Export$_{96} = 0$ $D_{96} = 0$ $D_{06} = 0$	Export$_{96} = 0$ $D_{96} = 0$
IV or OLS	IV Export using ($\Delta\tau_m$, $\Delta\tau_y$)	IV Export using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	IV both Import and Export using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	OLS	OLS	IV Import using TC
Import			5.1904*	0.1263***		-0.4408
			[2.656]	[0.030]		[0.501]
Export	1.4183	-0.9551	-1.0712			
	[1.471]	[1.218]	[1.855]			
$\ln(L_s^p/L_u^p)_{96}$	0.3732***	0.3796***	0.3377***	0.0039	0.0028	0.0075
	[0.026]	[0.026]	[0.039]	[0.005]	[0.005]	[0.007]
$d_{u,96}^p$	0.3596	0.3125	-0.0637	0.0011	-0.0178	0.0483
	[0.296]	[0.299]	[0.437]	[0.050]	[0.043]	[0.075]
$d_{s,96}^p$	-0.9668***	-1.0094***	-1.1348***	-0.0146	-0.0107	-0.0058
	[0.080]	[0.080]	[0.110]	[0.014]	[0.014]	[0.018]
No. Obs.	2,510	2,490	2,654	2,654	2,490	2,654

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included. The full specifications and their estimates are reported in Table D.5 in Appendix D.

Table 8: Import Decision Model using Logit for the Sample of Production Workers

	Full Sample				Initial Non-Importers			
	Coeff.	S.E.	Ave. Deriv.	S.E.	Coeff.	S.E.	Ave. Deriv.	S.E.
TC	-0.6998	[0.1169]	-0.0823	[0.0122]	-0.6328	[0.1690]	-0.0381	[0.0100]
$\Delta\tau_y$	0.0912	[0.1430]	0.0010	[0.0012]	0.0480	[0.2430]	0.0005	[0.0011]
$\Delta\tau_m$	0.0303	[0.1725]	-0.0016	[0.0020]	0.2874	[0.3055]	0.0009	[0.0020]
$TC \times \Delta\tau_y$	-0.0236	[0.2989]			0.0433	[0.4563]		
$TC \times \Delta\tau_m$	-0.2350	[0.3052]			-0.3865	[0.4043]		
$TC \times \log(\frac{L_s^p}{L_u^p})_{96}$	0.0174	[0.0903]			-0.0572	[0.1469]		
$\Delta\tau_y \times \log(\frac{L_s^p}{L_u^p})_{96}$	-0.0128	[0.1174]			-0.0953	[0.2084]		
$\Delta\tau_m \times \log(\frac{L_s^p}{L_u^p})_{96}$	0.1957	[0.1408]			0.0878	[0.2337]		
Export	0.5659	[0.0522]	0.1153	[0.0104]	0.5324	[0.0927]	0.0567	[0.0100]
Capital	0.4017	[0.0570]	0.0193	[0.0027]	0.3224	[0.0867]	0.0091	[0.0024]
Hicks-neutral φ	0.0996	[0.0458]	0.0163	[0.0074]	0.1225	[0.0642]	0.0112	[0.0059]
Foreign	0.1467	[0.0343]	0.0868	[0.0200]	0.1148	[0.0446]	0.0464	[0.0181]
R&D	0.0873	[0.0383]	0.0336	[0.0146]	0.0957	[0.0549]	0.0226	[0.0132]
Training	0.1409	[0.0488]	0.0301	[0.0104]	0.2124	[0.0687]	0.0249	[0.0082]
$\log(\frac{W_s}{W_u})$	-0.0344	[0.1826]	-0.0070	[0.0369]	-0.1158	[0.3090]	-0.0123	[0.0331]
$\log(\frac{L_s^p}{L_u^p})_{96}$	0.1765	[0.0877]	0.0130	[0.0064]	0.1559	[0.1489]	0.0062	[0.0060]
$d_{u,96}^p$	0.0967	[0.1237]	0.0197	[0.0251]	0.1667	[0.1933]	0.0178	[0.0206]
$d_{s,96}^p$	-0.0255	[0.0654]	-0.0052	[0.0132]	0.2780	[0.0887]	0.0296	[0.0096]
No. Obs.	6084				4648			

Notes: Estimates from the sample which uses the log of the production skill ratio as an outcome variable. Bootstrap standard errors are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included.

Table 9: Estimates of Skill Demand Equation (9) for the Sample of Production Workers

Dependent Var.	$\ln(L_s^p/L_u^p)_{06}$				$(W_sL_s^p/(W_uL_u^p + W_sL_s^p))_{06}$			
Sample	Full		$D_{96} = 0$		Full		$D_{96} = 0$	
Export	-0.2329	[0.0987]	-0.2508	[0.1313]	-0.0132	[0.0169]	0.0066	[0.0195]
Capital	0.1045	[0.0195]	0.1274	[0.0257]	0.0222	[0.0034]	0.0283	[0.0041]
Hicks-neutral φ	-0.3209	[0.0498]	-0.3693	[0.0597]	-0.0165	[0.0079]	-0.0223	[0.0106]
Foreign	-0.1517	[0.1331]	-0.2041	[0.1907]	-0.0460	[0.0234]	-0.0319	[0.0336]
R&D	0.0051	[0.0883]	-0.0668	[0.1268]	0.0171	[0.0152]	0.0312	[0.0210]
Training	0.1252	[0.0606]	0.0341	[0.0774]	0.0305	[0.0108]	0.0290	[0.0137]
$\log(\frac{W_s}{W_u})$	0.0891	[0.1931]	0.2043	[0.2334]				
$\log(\frac{L_s^p}{L_u^p})_{96}$	0.3908	[0.0292]	0.3753	[0.0393]	0.4585	[0.0242]	0.4536	[0.0276]
$d_{s,96}^p$	-1.0504	[0.0978]	-1.1576	[0.1211]				
$d_{u,96}^p$	0.0800	[0.3121]	-0.1029	[0.3968]				
$\log(\frac{L_s^p}{L_u^p})_{96} \times P(Z)$	-0.0928	[0.0850]	-0.4157	[0.2287]	-0.3287	[0.0768]	-0.5354	[0.1844]
$d_{s,96}^p \times P(Z)$	-0.0944	[0.6406]	-0.6318	[1.0293]				
$d_{u,96}^p \times P(Z)$	1.2672	[0.7590]	1.4262	[1.8273]				
No. Obs.	4151		2867		5839		4120	

Notes: The bootstrap standard errors are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included.

Table 10: Treatment Effects of Importing on Skill Demand

	Production				Non-Production			
Dep. Var.	$\ln(L_s^p/L_u^p)_{06}$		$(W_sL_s^p/(W_uL_u^p+W_sL_s^p))_{06}$		$\ln(L_s^n/L_u^n)_{06}$		$(W_sL_s^n/(W_uL_u^n+W_sL_s^n))_{06}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Full	$D_{96}=0$	Full	$D_{96}=0$	Full	$D_{96}=0$	Full	$D_{96}=0$
ATE	2.3529	3.1511	0.3308	0.5049	1.3971	0.7757	-0.2662	-0.2591
	[0.7227][a]	[1.2936]	[0.0930]	[0.1955]	[0.7361]	[1.2968]	[0.1289]	[0.1916]
	(1.35,3.76)[b]	(1.29,5.63)	(0.20,0.50)	(0.28,0.92)	(0.19,2.64)	(-1.47,2.78)	(-0.47,-0.05)	(-0.56,0.07)
TT	4.6086	5.5598	0.5408	1.3821	2.0388	2.0573	-0.6105	-0.8271
	[1.3570]	[1.9759]	[0.2002]	[0.8279]	[0.9177]	[1.9921]	[0.6213]	[0.5325]
	(3.06,7.38)	(3.49,9.77)	(0.24,0.88)	(0.65,3.36)	(0.57,3.56)	(-0.93,5.40)	(-1.55,0.49)	(-1.70,0.03)
TUT	1.9263	2.7775	0.2893	0.4206	1.2154	0.5339	-0.2140	-0.1876
	[0.7248]	[1.2470]	[0.0871]	[0.1866]	[0.7467]	[1.2751]	[0.1031]	[0.1689]
	(0.81,3.25)	(0.97,5.16)	(0.17,0.45)	(0.18,0.81)	(0.01,2.56)	(-1.78,2.43)	(-0.37,-0.02)	(-0.46,0.10)
MPRTE	3.6536	5.1268	0.4956	1.0027	1.846	1.8485	-0.5157	-0.7177
$(P_\alpha^*=P+\alpha)$	[1.0176]	[1.8048]	[0.1623]	[0.5523]	[0.8342]	[1.8284]	[0.3372]	[0.4497]
	(2.40,5.56)	(3.18,9.03)	(0.26,0.79)	(0.51,2.27)	(0.52,3.19)	(-1.00,5.06)	(-1.07,0.06)	(-1.45,0.02)
MPRTE	3.5027	5.0521	0.4866	0.8784	1.8242	1.7918	-0.4724	-0.6452
$(Z_\alpha^{k*}=Z^k+\alpha)$	[0.9643]	[1.7723]	[0.1525]	[0.4554]	[0.8252]	[1.7760]	[0.2372]	[0.3895]
	(2.28,5.28)	(3.16,8.89)	(0.27,0.76)	(0.44,1.94)	(0.51,3.16)	(-0.92,4.91)	(-0.86,-0.08)	(-1.27,-0.01)
PRTE	3.7075	5.2428	0.5595	1.099	1.9002	1.8519	-0.5209	-0.7051
$(TC^*=0.99TC)$	[2.2713]	[1.8444]	[2.1459]	[0.6211]	[1.2917]	[1.8366]	[1.5229]	[0.4366]
	(1.93,6.10)	(3.33,9.24)	(0.30,0.93)	(0.54,2.52)	(0.36,3.37)	(-0.92,5.10)	(-1.50,0.49)	(-1.43,0.01)
Support[c]	[0.010,0.837]	[0.006,0.483]	[0.010,0.852]	[0.007,0.480]	[0.009,0.853]	[0.006,0.466]	[0.004,0.852]	[0.007,0.466]
No. of Obs.[d]	4151	2867	5839	4120	1845	1237	5987	4103

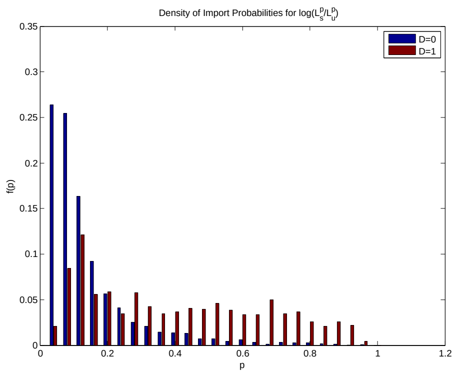
Notes: (a) The bootstrap standard errors are in square brackets. (b) The bootstrap equal-tailed 90 percent confidence intervals are in parentheses. (c) The minimum and the maximum values of support over which treatment effects are computed; various treatment effects are computed by restricting the weights to integrate to one in the restricted support, for which minimum and maximum values are determined by the 1^{st} percentile and the 99^{th} percentile of observations in the common support, respectively. (d) The sample size for estimating the MTE curve.

Table 11: Robustness Check: Treatment Effects of Importing on Skill Demand for Production Workers using the Sample of Initial Non-Importers ($D_{96} = 0$)

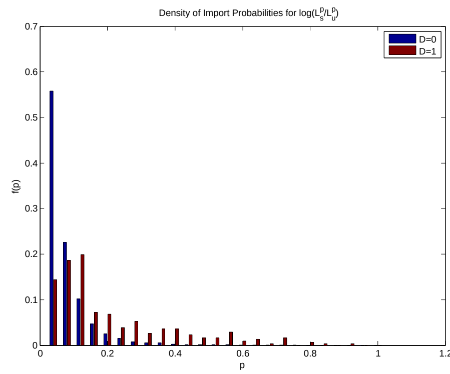
Dep. Var.	$\ln(L_s^p/L_u^p)_{06}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Sample of $\text{Export}_{96} = 0$ and $\text{Export}_{06} = 0$	Replace φ with TFP	Use Sieve in place of Local Poly.	No Interaction with Z	Treatment Effects over Common Support	Use Dummy for Standards in place of D_{06} [(e)]
ATE	3.7063	1.7604	2.7416	2.3764	2.5906	2.1017
	[3.4275][(a)]	[1.1411]	[1.3425]	[0.9677]	[1.4769]	[1.1434]
	(0.35,8.62)[(b)]	(-0.49,3.31)	(0.88,5.11)	(0.88,4.08)	(0.98,5.39)	(0.47,4.05)
TT	5.9506	3.7704	5.4234	6.5888	5.5811	4.4938
	[4.3382]	[1.6654]	[2.9006]	[3.0328]	[2.0474]	[1.8976]
	(0.28,13.61)	(1.10,6.73)	(1.46,10.85)	(2.04,12.06)	(3.08,9.71)	(2.16,8.11)
TUT	3.1992	1.4359	2.3237	1.8249	2.2983	1.6421
	[3.6630]	[1.1184]	[1.2822]	[0.8520]	[1.5203]	[1.0862]
	(0.01,7.71)	(-0.78,2.89)	(0.43,4.46)	(0.45,3.31)	(0.65,5.22)	(-0.07,3.42)
MPRTE	5.2086	3.4361	4.9549	5.3837	5.1309	3.9486
($P_\alpha^* = P + \alpha$)	[3.8015]	[1.5436]	[2.3563]	[2.3239]	[1.8701]	[1.6616]
	(0.23,11.86)	(0.86,6.09)	(2.08,9.63)	(1.81,9.43)	(2.85,8.85)	(1.86,7.16)
MPRTE	4.9763	3.3787	4.8751	5.0801	5.0526	3.9109
($Z_\alpha^{k*} = Z^k + \alpha$)	[3.6241]	[1.5188]	[2.2353]	[2.1372]	[1.8359]	[1.6407]
	(0.23,11.16)	(0.83,5.98)	(2.14,9.35)	(1.90,8.73)	(2.84,8.72)	(1.82,7.10)
PRTE	5.3081	3.5216	5.0776	5.6964	5.2942	4.0116
($TC^* = 0.99TC$)	[4.8633]	[1.5722]	[2.5513]	[2.4664]	[50.5908]	[1.9699]
	(0.55,12.44)	(0.93,6.30)	(1.81,10.06)	(2.02,10.10)	(2.79,9.29)	(1.45,7.45)
Support[(c)]	[0.0033,0.2495]	[0.0052,0.4951]	[0.0064,0.4834]	[0.0063,0.4812]	[0.0059,0.7347]	[0.0163,0.7370]
No. of Obs.[(d)]	2007	2904	2868	2871	2868	2208

Notes: (a) The bootstrap standard errors are in square brackets. (b) The bootstrap equal-tailed 90 percent confidence intervals are in parentheses. (c) The minimum and the maximum values of support over which treatment effects are computed; various treatment effects are computed by restricting the weights to integrate to one in the restricted support, for which minimum and maximum values are determined by the 1^{st} percentile and the 99^{th} percentile of observations in the common support, respectively. (d) The sample size for estimating the MTE curve. (e) We use the sample of $\text{Export}_{96} = 0$ and $\text{Export}_{06} = 0$ in column (6) as in column (1).

Figure 1: Support of Estimated Propensity Scores

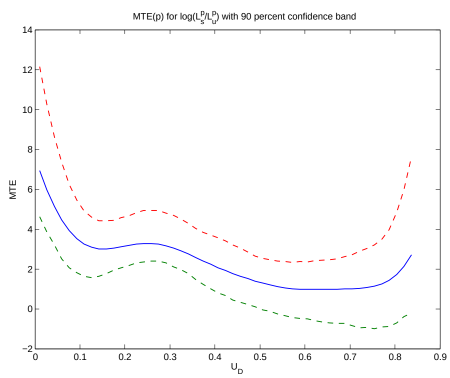


(a) Full Sample

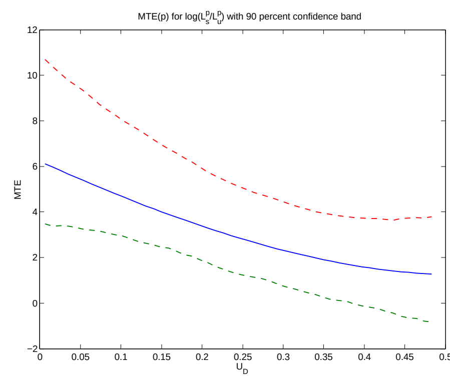


(b) Subsample of Initial Non-Importers

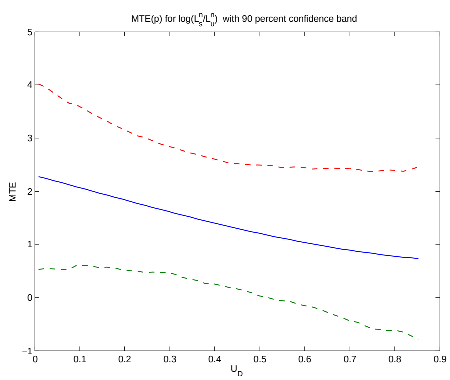
Figure 2: Estimated MTE for Dependent Variables $\ln(L_s^p/L_u^p)$ and $\ln(L_s^n/L_u^n)$



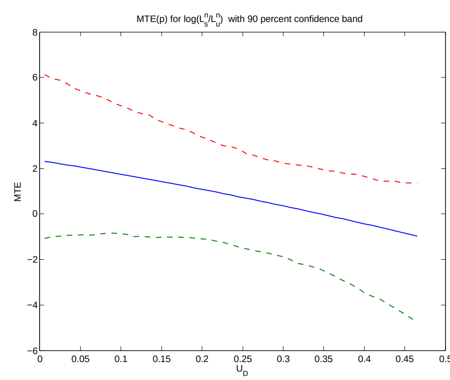
(a) Production Workers, Full Sample



(b) Production Workers, Initial Non-Importers



(c) Non-Production Workers, Full Sample



(d) Non-Production Workers, Initial Non-Importers

A Data Description

This section describes the construction of the variables used for the empirical analysis. Specifically, it includes the description of variables coming from manufacturing survey data, household survey data and the construction of instrumental variables.

A.1 Manufacturing Plant Data

Our plant level data comes from the Indonesian manufacturing census (Large and Medium Industrial Statistics) in years 1994-1996 and 2004-2007. This survey data covers all manufacturing plants in Indonesia with at least 20 employees. Key variables used in our study are described below.

A.1.1 Labor

For each plant, the survey records the education levels of all production and non-production workers. This dimension of the data allows us to compute the number of skilled and unskilled workers in each occupation category. As discussed in the main text we define a skilled worker as a worker with a high school diploma or more. Using this threshold we count the number of skilled and unskilled workers for each production category and each plant.

A.1.2 Intermediate Goods and Capital

In order to estimate plant-specific productivity, we also need the intermediate goods and capital used for production. Intermediate goods includes imported raw materials, domestically purchased raw materials and expenditures on energy. The wholesale price index for manufactured goods is used to convert nominal values into real values.

We compute the real value of capital at the beginning of year t as

$$K_{it} = building_{it}/P_t^{build} + machine_{it}/P_t^{mach} + vehicle_{it} \times 100/P_t^{vehic} + (rent_{it}/0.1)/P_t^{rent},$$

where $building_{it}$, $machine_{it}$, and $vehicle_{it}$ are the nominal value of buildings, machines, and vehicles at the beginning of year t; $rent_{it}$ is equal to the reported value of rental payments for buildings and machines, where we divide the rental value by the depreciation rate (10 percent) to get the appropriate capitalized value. The capital price indices are obtained from Badan Pusat Statistik (BPS).[15] Since rent is only paid for buildings and machines, we compute price index for rented capital as

$$P_t^{rent} = \frac{\sum_i building_{it}}{\sum_i (building_{it} + machine_{it})} \times P_t^{build} + \frac{\sum_i machine_{it}}{\sum_i (building_{it} + machine_{it})} \times P_t^{mach}.$$

When the capital values are not reported in 1996 or 2006, we use the reported values of capital in 1994, 1995 and 1997 for constructing the 1996 capital value, and similarly, the reported values of capital in 2004, 2005 and 2007 for constructing the 2006 capital value by assuming $K_{it} = 0.9K_{it-1} + Investment_{it-1}$ with $Investment_{it} = Investment_{it}^{buildings} + Investment_{it}^{machines} + Investment_{it}^{vehicles}$, where $Investment_{it}^{building}$, $Investment_{it}^{machines}$, and $Investment_{it}^{vehicles}$ are the real values of net investment for buildings, machines, and vehicles in year t.

[15]Specifically, we use the price indices for construction goods, imported and domestic machines, and vehicles. The imported and domestic machines price indices are weighted according to the input-output table for manufactured goods to get one price index for machines. The building price index covers the period 1996-2006 and is extended to 2007; machine and vehicle price data only covers 1998 to 2005 and is extended to the period 1996-2007. The extension from 1998 to 1996 relies on the wholesale price of capital goods which is available during the 1992-1999 period. The GDP deflator for construction goods, machines and vehicles is used to extend the original price index to 2007.

Some plants do not report capital values in any year between 2004 and 2007. For those plants, we impute the values of capital as follows. First, using the plant observations in 2005 for which capital values are constructed from the data between 2004 and 2007, we run the OLS regression

$$\log K_{i,2005} = X'_{i,2005}\alpha + \epsilon_{i,2005},$$

where $K_{i,2005}$ is the beginning-of-period capital in 2005; X_{it-1} includes a constant, the ratio of investment to capital, the log of production workers, the log of non-production workers, the log of output, the log of intermediate goods, an import dummy, province dummies, industry dummies, plant age, plant age squared, a dummy variable for positive investment, a dummy variable for no hiring of production workers, and a dummy variable for no hiring of non-production workers. Then, given the OLS estimate of α, $\hat{\alpha}$, we compute the imputed value of capital at the beginning of year 2006 for plants with missing capital values as

$$K^{impute}_{i,2006} = 0.9\exp(X'_{i,2005}\hat{\alpha}) + Investment_{i,2005}.$$

For the sample of initial non-importers, we use the imputed values of capital for 11 percent of observations. For plants with missing capital values in 1996, we similarly construct the imputed value of capital at the beginning of year 1996 using 1995 data.

A.1.3 Other Variables

Other plant information contained in the data includes the percentage of foreign ownership, total expenses on research and development (R&D), and total expenses on training. Dummies variables for foreign ownership, R&D and training are defined as whether the above mentioned variables are greater than zero.

A.2 Regional Data

A.2.1 Wages

We use the household survey data (SAKERNAS—Indonesian Labour Force Survey) to construct local market wages for skilled and unskilled workers for each regency (kabupaten/kota) in Indonesia. The basic measure of a wage is the average wage of workers who are 25-35 years old at different skill levels (more or less than high-school education) in the regency. However, the relative wage computed using this basic measure may not measure the true skill premium since unskilled workers will generally have had more work experience than skilled workers within same age range. To solve this problem, we use Mincer regressions to get the return to skill. Specifically, for each regency, we regress the individual level log wage over experience, experience squared and a skill dummy and use the coefficient on the skill dummy as the log of the wage premium in that regency. The plant-level wage share of skilled workers in the total wage bills for occupation $j \in \{p, n\}$ is computed as $\frac{W_s L^j_s}{W_s L^j_s + W_u L^j_u} = \frac{(W_s/W_u)L^j_s}{(W_s/W_u)L^j_s + L^j_u}$, where W_s/W_u is the estimated wage ratio for the regency in which a plant is located.

A.2.2 Distance to Port

To form this instrumental variable, we use the location information of individual plants. Indonesia is comprised of 33 provinces which are administratively subdivided in to 429 regencies in our data. The dataset includes the location of the surveyed plants down to the regency level. Due to the detailed administrative divisions, the variation contained in the plant location data is informative. Among all ports in Indonesia, 2 can be considered large, 16 medium and all others remaining are either small or very small.[16] The 18 large or medium sized ports are chosen to be the main destinations for our constructed

[16] Source of port information: World Port Source.

measure of transportation costs. Specifically, given these destinations, and taking the geographical features of Indonesia into consideration, we compute the least-cost path from the center of every regency to its nearest port by ArcGIS. The calculation divides the entire country into cells with size 1 km^2 where each cell contains a value representing the average elevation of that area. The travel cost of each cell depends on the slope from the cell to its adjacent cells and whether the cell locates on land or on sea. ArcGIS determines the optimal route for each cell by finding the least-accumulative-cost path to its nearest major port. The transportation cost for a regency is approximated by the the accumulative cost along the optimal route from the center cell of the regency. For each plant, the proxy for its transportation cost is the transportation cost of the regency in which the plant is located. Details about the process of computing this cost measure are described in the following paragraphs.

Three types of data are used in ArcGIS to generate the transportation cost: raster data (R), point data (P) and table data (T). Raster data consists of a matrix of cells (pixels) organized into a grid where each cell contains a value representing information. In our data, each cell represents a 1 km^2 square in the real world. Point data contains information for specific points. Each point is composed of one coordinate pair representing its location on the earth. Table data is used to store the attributes (e.g. names, locations, temperatures, etc.) of features.

There are three main steps for computing the transportation cost. First, generate the cost raster for Indonesia which defines the cost to move planimetrically through each cell according to geographical features. Second, given a cost raster and the main ports as destination points, the "Cost Distance" tool generates the raster data in which the least accumulated cost distance for each cell to its nearest destination is calculated. Lastly, to get the measure of the transportation cost for each regency, we extract the cost distance value for the cells located in the center of the regencies from the raster data obtained from second step. Figure A.1 displays the process of this calculation. The ellipses in the flowchart represent data while the round-cornered squares represent tools.

Step 1. The travel cost of each cell depends on the slope from the cell to its adjacent cells and whether the cell is located on land or sea. "Elevation-full" is the Indonesia elevation data, the value of a cell in this raster data indicates the average elevation in the 1 km^2. Cells in the sea take a value of zero. The "SLOPE" tool generates the slope layer "Elevation Slope", in which a cell value indicates the maximum rate of change between the cell and its neighbors. A road which traverses less steep slopes is preferable. We reclassify the slope layer, slicing the values into 10 equal intervals. A value of 10 is assigned to the most costly slopes (steepest) and 1 is assigned to the least costly slope (flattest), values in between are ranked linearly. "Reclass Slope" is the raster data after re-classification. Each cell value between 1 and 10 indicates the difficulty of traveling over it. One problem with this surface is that traveling across the sea is considered costless since the elevation is zero (and so are the slopes) everywhere on the sea. To solve this problem, another layer "Sea" is created. The "Sea" raster assigns value 0 for land and 1 for sea. The last step for generating the cost raster overlays the rasters "Reclass Slope" and "Sea" using a common measurement scale and weights 50 percent on each layer. Specifically, scale values of the "Reclass Slope" layer are unchanged (10 for steepest and 1 for flattest), and scale values for "Sea" layer are set to be 1 for land (low cost) and 10 for sea (high cost), thus, the cost of travelling over cell i is

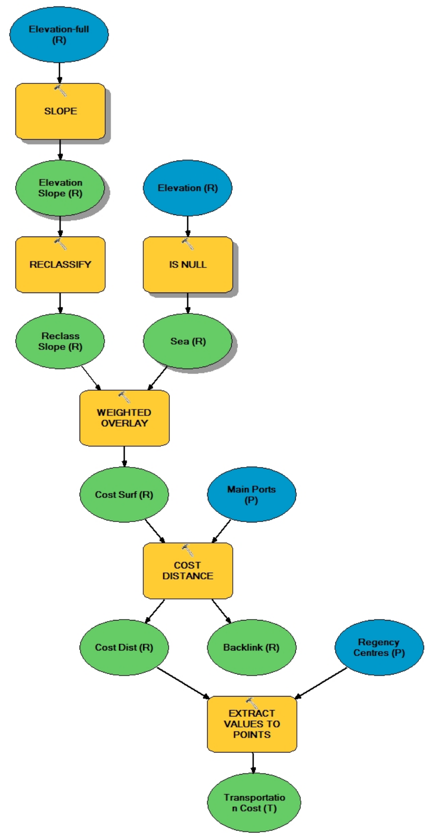
$$Cost_i = 0.5 \times ReclassSlope_i + 0.5 \times 10^{Sea_i} \tag{10}$$

Putting all the cells on map forms the raster data "Cost Surf".

Step 2. Given the 18 main ports ("Main Ports") as destinations, the "COST DISTANCE" tool calculates the accumulated distance from each cell to its nearest destination along the optimal path, using the "Cost Surf" data obtained in step 1 to measure the cost of passing cells. The resulting raster data "Cost Dist" reports the transportation cost of all the cells. Figure A.2 presents this cost surface. Red to purple and white represent highest to lowest transportation costs, blue boat symbols indicate the main ports. It is clear that the regencies in west Indonesia face lower transportation costs as there are more ports while regencies in the east are subject to high transportation costs. For each cell, "Backlink" indicates the neighbor that is the next cell on the least accumulative cost path to the nearest destination. This direction information is not used in the empirical analysis, but it helps draw the paths when necessary.

Step 3. We extract the values of the cells located in the center of administrative regencies from the transportation cost map "Cost Dist" using the tool "EXTRACT VALUES TO POINTS."

Figure A.1: Process of Measuring Transportation Cost



Notes: This figure displays the process of calculating the transportation cost for the regencies in Indonesia using ArcGIS. The ellipses in the flowchart represent data and the round-cornered squares represent tools.

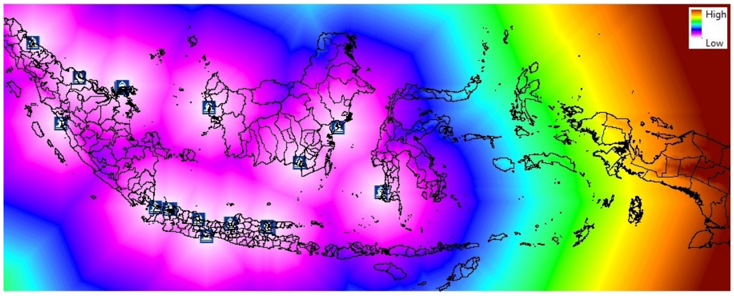
A.2.3 Tariffs

The plant-level manufacturing data are matched with detailed industry-level tariff data from Amiti and Konings (2007). Specifically, each plant is assigned a 5-digit code in each year and is matched to output and input tariff rates with the same 5-digit code in the same year. Figure A.3 demonstrates that output tariffs have fallen across most industries in Indonesia over the 1991-2001 period and that there is substantial variation in the initial tariff levels and the subsequent fall across 5-digit industries over the following decade.

B Estimating MTE and Treatment Effects

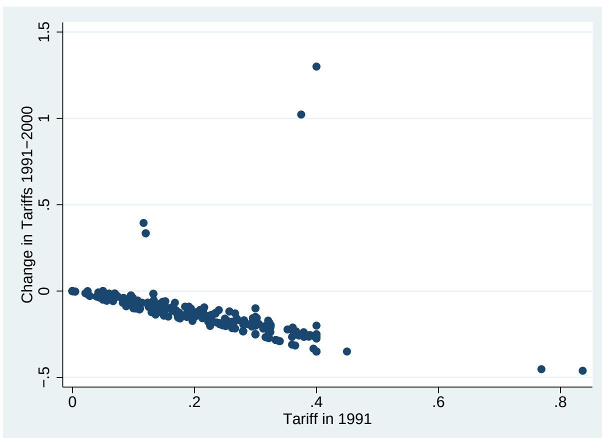
We estimate γ, δ, and $K(p)$ by a partially linear regression of S on X and $P(Z)$ (Robinson, 1988) as follows.

Figure A.2: Map of Transportation Cost



Notes: This map presents the cost surface. Red to purple and white represent highest to lowest transportation cost, blue boat symbols indicate the main ports. It is clear that the regencies in west Indonesia face lower transportation cost as there are more ports while regencies in the east are subject to high transportation costs.

Figure A.3: Change in Tariffs, 1991-2000, Relative to 1991 Level



Notes: Tariffs fell over the sample period in all industries with the exception of the liquors and wine industries (ISIC codes 31310, 31320) and rice milling industries (ISIC codes 31161, 31169).

Step 1: We estimate $P(Z)$ using a logit specification as described in the main text. Denote the estimated value by "hat" notation so that $\hat{P}(Z)$ denotes the estimate of $P(Z)$.

Step 2: Using the subsample of observations for which the outcome variable is measurable and for which estimated propensity scores $\hat{P}(Z_i)$'s are on the estimated common support, we estimate $E[S|P(Z)]$, $E[X|P(Z)]$, and $E[\tilde{X}|P(Z)]$ by local linear regressions of S, X, and $\tilde{X}$ on $\hat{P}(Z)$, respectively, where we use a normal kernel and choose their bandwidths by "leave-one-out" cross-validation.

Step 3: By regressing $S-\hat{E}[S|P(Z)]$ on $X-\hat{E}[X|P(Z)]$ and $P(Z)(\tilde{X}-\hat{E}[\tilde{X}|P(Z)])$ without an intercept, we obtain the estimate of γ and θ.

Step 4: We estimate $K(P(Z))$ and $K'(P(Z))$ by using a local quadratic regression of $S-X'\hat{\gamma}-\hat{P}(Z)\tilde{X}'\hat{\theta}$ on $\hat{P}(Z)$, where we use cross-validation to choose the bandwidth for the local quadratic regression.

To avoid numerical singularity, all continuous variables in Z, X, and $\tilde{X}$ are standardized by subtracting their means and then dividing by their sample standard deviations while all dummy variables are transformed into $\{-1,1\}$. Table B.1 reports the bandwidth choices using the standardized variables for Step 2 and Step 4. We set the maximum value of the bandwidth to one-half of the length of the common support of $\hat{P}(Z|D=0)$ and $\hat{P}(Z|D=1)$.

In column (3) of Table 11, we use a sieve estimator to estimate the partial linear regression. Specifically, we estimate $E[S|P(Z)]$, $E[X|P(Z)]$, and $E[\tilde{X}|P(Z)]$ in Step 2 by regressing S, X, and $\tilde{X}$ on the fourth order polynomials of $\hat{P}(Z)$ while we estimate $K(P(Z))$ and $K'(P(Z))$ by regressing $S-X'\hat{\gamma}-\hat{P}(Z)\tilde{X}'\hat{\theta}$ on the fourth order of polynomials in $\hat{P}(Z)$.

As Heckman and Vytlacil (2005, 2007a, 2007b) and Carneiro, Heckman, and Vytlacil (2010) show, various treatment effects conditional on X can be expressed as weighted averages of the MTE.

$$\begin{aligned}
&ATE(x)=\int_0^1 \Delta^{MTE}(x,p)dp, && TT(x)=\int_0^1 \Delta^{MTE}(x,p)h_{TT}(x,p)dp,\\
&TUT(x)=\int_0^1 \Delta^{MTE}(x,p)h_{TUT}(x,p)dp, && PRTE(x)=\int_0^1 \Delta^{MTE}(x,p)h_{PRTE}(x,p)dp,\\
&MPRTE(x)=\int_0^1 \Delta^{MTE}(x,p)h_{PRTE}(x,p)dp, &&
\end{aligned} \tag{11}$$

where

$$\begin{aligned}
&h_{TT}(x,p)=\frac{1-F_P(p|X=x)}{E(P|X=x)}, \quad h_{TUT}(x,p)=\frac{F_P(p|X=x)}{E(1-P|X=x)},\\
&h_{PRTE}(x,p)=\frac{F_{P^*}(p|X=x)-F_P(p|X=x)}{E(P|X=x)-E(P^*|X=x)},\\
&h_{MPRTE}(x,p)=\lim_{\alpha\to 0}\frac{F_{P^*_\alpha}(p|X=x)-F_P(p|X=x)}{E(P|X=x)-E(P^*_\alpha|X=x)}=\frac{(\partial/\partial\alpha)F_{P^*_\alpha}(p|X=x)|_{\alpha=0}}{\int(\partial/\partial\alpha)F_{P^*_\alpha}(p|X=x)|_{\alpha=0}dp}.
\end{aligned} \tag{12}$$

$F_P(\cdot|X=x)$ and $F_{P^*}(\cdot|X=x)$ are the cumulative distributions of P and P^*, respectively, conditional on $X=x$, where P^* is the probability of importing under an alternative policy.

Treatment effects can be computed by integrating conditional treatment effects in (11) using the appropriate distribution of X. Because X is high dimensional, however, it is not computationally feasible to estimate the conditional density function of P given X. For this reason, exploiting the fact that $f_p(P|X)=f_p(P|X'\theta)$ implies $E[\log(P/(1-P))|X]=E[\log(P/(1-P))|X'\theta]$, we regress $\log(\hat{P}/(1-\hat{P}))$ on X and obtain a single index of X, $X'\hat{\theta}$. The conditional density function of P given $X'\theta$, denoted by $f_P(p|x'\theta)$, is estimated by the ratio of the joint density of P and $X'\hat{\theta}$ to the marginal density of $X'\theta$ using 'double-kernel' local linear regression, where we choose the bandwidth by the cross-validation following the suggestion of Fan and Yim (2004).

We compute weights $h_{TT}(x'\theta,p)$, $h_{TUT}(x'\theta,p)$, $h_{PRTE}(x'\theta,p)$, and $h_{MPRTE}(x'\theta,p)$ as $h_{TT}(x,p)$, $h_{TUT}(x,p)$, $h_{PRTE}(x,p)$, and $h_{MPRTE}(x'\theta,p)$ in the formula (12) but using $F_P(p|X'\theta=x'\theta)=\int_0^p f_P(u|X'\theta=$

$x'\theta)du$ in place of $F_P(p|X=x)$. To apply (11) to compute treatment effects conditioning on the single index $X'\theta$, we evaluate the MTE at $X'\theta = x'\theta$ instead of $X = x$. To do so, we estimate $E[\tilde{X}'\delta|X'\theta]$ by local linear regression and define the MTE at $X'\theta = x'\theta$ as $\hat{\Delta}^{MTE}(x'\theta, p) = \hat{E}[\tilde{x}'\delta|X'\theta = x'\theta] + \hat{K}'(p)$. Integrating $\hat{\Delta}^{MTE}(x'\theta, p)$ using weights $h_{TT}(x'\theta, p)$, $h_{TUT}(x'\theta, p)$, $h_{PRTE}(x'\theta, p)$, and $h_{MPRTE}(x'\theta, p)$ gives our estimates of the $TT(x'\theta)$, $TUT(x'\theta)$, $PRTE(x'\theta)$, and $MPRTE(x'\theta)$. To obtain the unconditional version of treatment effects, we integrate $X'\theta$ from $TT(X'\theta)$, $TUT(X'\theta)$, $PRTE(X'\theta)$, and $MPRTE(X'\theta)$ using the marginal distribution of $X'\theta$, denoted by $f_{X'\theta}(x'\theta)$, which is estimated by local linear regression. The last four rows of Table B.1 report the bandwidth choices associated with estimating $f_P(p|x'\theta)$, $f_{X'\theta}(x'\theta)$, and $E[\tilde{X}'\delta|X'\theta]$.

Finally, because the full support condition is violated, we report estimates of ATE, TT, TUT, PRTE, and MPRTE when we restrict the weights to integrate to one in the restricted support of the MTE as described in the main text. As discussed in Heckman and Vytlacil (2005) and Carneiro, Heckman and Vytlacil (2010), the PRTE cannot be identified without strong support conditions. We compute the estimate of what the PRTE would be when we restrict the support of P and P^* to the restricted support for which minimum and maximum values are given by the 1^{st} and the 99^{th} percentiles of the common support, where the maximum value of P^* is set to the maximum value of the restricted support when the value of P^* is above the maximum value of the support.

We use 500 bootstrap replications to construct equal-tailed bootstrap confidence bands for $\hat{\Delta}^{MTE}(x'\theta, p)$ and the standard errors for treatment effects. In each bootstrap iteration we re-estimate $P(Z)$ so all standard errors account for the fact that $P(Z)$ is estimated.

Table B.1: Bandwidth Choices by Cross-validation

Dep. Var.	$\ln(L_s^p/L_u^p)_{06}$		$(\frac{W_s L_s^p}{W_u L_u^p + W_s L_s^p})_{06}$	
	(1)	(2)	(3)	(4)
Sample	Full	$D_{96}=0$	Full	$D_{96}=0$
Step 2: $E[S\|P]$	0.07	0.03	0.05	0.01
$E[\ln(L_s^p/L_u^p)_{96}\|P]$	0.19	0.07	0.05	0.03
$E[\text{Capital}\|P]$	0.03	0.11	0.03	0.03
$E[\varphi\|P]$	0.07	0.15	0.03	0.05
$E[\text{Foreign}\|P]$	0.11	0.23	0.13	0.23
$E[\text{R\&D}\|P]$	0.11	0.03	0.47	0.17
$E[\text{Training}\|P]$	0.03	0.07	0.05	0.03
$E[\text{Export}\|P]$	0.15	0.11	0.15	0.13
$E[d_{s,96}^p\|P]$	0.03	0.05		
$E[d_{u,96}^p\|P]$	0.46	0.36		
$E[\ln(W_s/W_u)\|P]$	0.03	0.05		
$E[\text{industry/province}\|P]^{(a)}$	0.03	0.03	0.01	0.01
Step 4: $E[S - X'\gamma - P(Z)\tilde{X}'\theta\|P]$	0.09	0.23	0.17	0.03
Bandwidth for P of $f_P(p\|x'\theta)$	0.005	0.005	0.005	0.005
Bandwidth for $X'\theta$ of $f_P(p\|x'\theta)$	0.02	0.01	0.01	0.01
Bandwidth for $f_{X'\theta}(x'\theta)$	0.03	0.02	0.02	0.01
Bandwidth for $E[\tilde{X}'\delta\|X'\theta]$	0.50	0.05	0.03	0.03

Notes: Columns (1)-(4) reports the cross-validation bandwidth choices that are used to estimate the treatment effects reported in columns (1)-(4) of Table 10, respectively. (a) We choose the common bandwidth for industry/province dummies by minimizing the sum of cross-validation criterion functions over industry/province dummies.

C Estimating Hicks-Neutral Productivity

Our model implies that Hicks-neutral productivity differences are potentially among the most important determinants of plant-level import decisions. Unfortunately, the data do not provide a convenient measure of Hicks-neutral productivity. Moreover, standard productivity estimation methods do not consider how we might separately identify skill-biased and Hicks-neutral productivity.[17] Accordingly, we develop an extension of the control function methods pioneered by Olley and Pakes (1996) [OP, hereafter], Levinsohn and Petrin (2003) [LP, hereafter] and Ackerberg, Caves and Frazer (2006), among others, to estimate a Hicks-neutral productivity series for each plant in our data.[18]

We assume that the firm's production function is specified as

$$Y_{it} = e^{\varepsilon_{it}} Q_{it}, \quad \text{where} \quad Q_{it} = e^{\alpha_0 + \omega_{it}} K_{it}^{\alpha_k} M_{it}^{\alpha_m} L_{p,it}^{\alpha_p} L_{n,it}^{\alpha_n} \tag{13}$$

where ω_{it} is the part of the Hicks-neutral productivity shock that is observed/anticipated by firm i at the time which it makes input decisions while ε_{it} captures either measurement error or an *iid* unanticipated shock that is not observed at the time which it makes input decisions. The variables $L_{p,it}$ and $L_{n,it}$ represent the aggregate labor inputs for production and non-production activities, respectively, and are defined by

$$L_{j,it} = \left((A_j L_{j,it}^s)^{\frac{\sigma_j - 1}{\sigma_j}} + (L_{j,it}^u)^{\frac{\sigma_j - 1}{\sigma_j}} \right)^{\frac{\sigma_j}{\sigma_j - 1}} \quad \text{for } j = p, n. \tag{14}$$

Here, $L_{j,it}^s$ and $L_{j,it}^u$ represent the number of skilled workers and that of unskilled workers, respectively, in occupation j, where the subscript "p" indicates production workers while the subscript "n" captures non-production workers. We assume that ω_{it} follows a first order Markov process.

To estimate the production function coefficients, including the elasticity of substitution parameters, we use the implications of plant profit maximization behavior.[19] The first order conditions with respect to $L_{j,it}^u$ and $L_{j,it}^s$ are given by

$$\frac{W_t^u L_{j,it}^u}{Q_{it}} = \alpha_j \frac{(L_{j,it}^u)^{\frac{\sigma_j - 1}{\sigma_j}}}{(A_j L_{j,it}^s)^{\frac{\sigma_j - 1}{\sigma_j}} + (L_{j,it}^u)^{\frac{\sigma_j - 1}{\sigma_j}}} \quad \text{and} \quad \frac{W_t^s L_{j,it}^s}{Q_{it}} = \alpha_j \frac{(A_j L_{j,it}^s)^{\frac{\sigma_j - 1}{\sigma_j}}}{(A_j L_{j,it}^s)^{\frac{\sigma_j - 1}{\sigma_j}} + (L_{j,it}^u)^{\frac{\sigma_j - 1}{\sigma_j}}}, \tag{15}$$

respectively, so that

$$\left(\frac{L_{j,it}^u}{L_{j,it}^s} \right)^{\frac{1}{\sigma}} A_j^{\frac{\sigma_j - 1}{\sigma_j}} = \frac{W_t^s}{W_t^u} \quad \text{for } j = p, n, \tag{16}$$

where W_t^s and W_t^u represent the wages in year t for skilled and unskilled workers, respectively. We assume that there is no unanticipated ex-post shock to A_j, W_t^s, and W_t^u. Substituting (16) into (14), we get

$$L_{j,it} = X_{j,it}^{-\frac{\sigma_j}{\sigma_j - 1}} L_{j,it}^u, \quad \text{where} \quad X_{j,it} \equiv \frac{W_t^u L_{j,it}^u}{W_t^s L_{j,it}^s + W_t^u L_{j,it}^u}.$$

Substituting the above equation for $L_{j,it}$ into (13) and taking the logarithm gives

$$y_{it} = \alpha_{0,t} + \alpha_k k_{it} + \alpha_m m_{it} + \alpha_p l_{p,it}^u + \beta_p x_{p,it} + \alpha_n l_{n,it}^u + \beta_n x_{n,it} + \omega_{it} + \epsilon_{it} \tag{17}$$

where $\beta_j = -\frac{\sigma_j \alpha_j}{\sigma_j - 1}$ for $j = p, n$, and lower case letters represent the logarithm of the upper case letters (e.g., $y_{it} \equiv \ln(Y_{it})$). Note that, if we can consistently estimate α_j and β_j, then we also have a consistent estimate of σ_j because $-\beta_j / \alpha_j = \frac{\sigma_j}{\sigma_j - 1}$.

We recover the estimates in two stages. In the first stage, following LP, we write ω_{it} as a function of m_{it}, k_{it}: $\omega_{it} = \omega_t^*(m_{it}, k_{it})$. Taking an expectation of (17) conditional on (m_{it}, k_{it}), and subtracting it

[17] Doraszelski and Jaumandreu (2012) is a key exception.

[18] Other important contributions to this literature include Wooldridge (2009), De Loecker (2011), De Loecker et al. (2012) and Doraszelski and Jaumandreu (2013).

[19] Our method is broadly based on the ideas contained in Gandhi, Navarro, and Rivers (2011), but our production function is specified using a simple Cobb-Douglas form with CES aggregators for production and non-production labor inputs so that our analysis is substantially simpler than theirs.

from (17) gives

$$y_{it} - E[y_{it}|m_{it}, k_{it}] = \alpha_p\{l^u_{p,it} - E[l^u_{p,it}|m_{it}, k_{it}]\} + \beta_p\{x_{p,it} - E[x_{p,it}|m_{it}, k_{it}]\} + \alpha_n\{l^u_{n,it} - E[l^u_{n,it}|m_{it}, k_{it}]\} + \beta_n\{x_{n,it} - E[x_{n,it}|m_{it}, k_{it}]\} + \epsilon_{it}. \quad (18)$$

where $E[\epsilon_{it}|m_{it}, k_{it}] = 0$ under the assumption that ϵ_{it} is mean zero random variable and that ϵ_{it} is not observed yet when a plant makes intermediate input decision.

The parameters α_p, β_p, α_n, and β_p are estimated by (i) first estimating the functions $E[y_{it}|m_{it}, k_{it}]$, $E[\ell^u_{p,it}|m_{it}, k_{it}]$, $E[\ell^u_{n,it}|m_{it}, k_{it}]$, $E[x_{p,it}|m_{it}, k_{it}]$ and $E[x_{n,it}|m_{it}, k_{it}]$ and then (ii) running a no-intercept OLS regression of (18) using the estimate of the conditional expectation terms. Note that, even though we consider the possibility of endogenous exiting, the first stage procedure is identical to that of LP.

In the second stage we identify the remaining production function parameters α_k and α_m. To accomplish this, we first define

$$\phi_t(m_{it}, k_{it}) \equiv \alpha_{0,t} + \alpha_k k_{it} + \alpha_m m_{it} + \omega^*_t(m_{it}, k_{it})$$

and

$$x_{it} \equiv y_{it} - \{\alpha_p l^u_{p,it} + \beta_p x_{p,it} + \alpha_n l^u_{n,it} + \beta_n x_{n,it}\}.$$

Further, let $\chi_{it} = 1$ indicate plant survival in year t. We assume that a firm stays in the market if and only if $\omega_{it} \geq \underline{\omega}_t(k_{it})$ as in OP. Then, we may write (17) as

$$\begin{aligned} x_{it} &= \alpha_{0,t} + \alpha_k k_{it} + \alpha_m m_{it} + E[\omega_{it}|\omega_{it-1}, \chi_{it} = 1] + \xi_{it} + \epsilon_{it} \\ &= \alpha_k k_{it} + \alpha_m m_{it} + g_t(\underline{\omega}_t(k_{it}), \omega_{it-1}) + \xi_{it} + \epsilon_{it} \end{aligned} \quad (19)$$

where $\xi_{it} = \omega_{it} - E[\omega_{it}|\omega_{it-1}, \chi_{it} = 1]$ and $g_t(\underline{\omega}_t(k_{it}), \omega_{it-1}) \equiv \alpha_{0,t} + E[\omega_{it}|\omega_{it-1}, \chi_{it} = 1]$.

The survival probability conditional on ω_{t-1} is given by

$$\begin{aligned} \Pr\{\chi_{it} = 1|\omega_{it-1}, k_{it-1}, m_{it-1}\} &= \Pr\{\omega_t \geq \underline{\omega}_t(k_{it})|\omega_{it-1}, m_{it-1}, k_{it-1}\} \\ &= \int_{\underline{\omega}_t(k_{it}(m_{it-1}, k_{it-1}))}^{\infty} F(d\omega_{it}|\omega^*_{t-1}(m_{it-1}, k_{it-1})) \\ &= P^{\chi}_{it}. \end{aligned} \quad (20)$$

where $F(\cdot)$ represents the law of motion for ω_{it}. The capital stock follows $k_{it} = (1-\delta)k_{it-1} + \iota_{it}$ where ι_{it} is the amount of investment between $t-1$ and t, ι_{it} captures net investment, δ is the depreciation rate, and we assume that ι_{it} is a function of $(\omega_{it-1}, k_{it-1}) = (\omega^*_t(m_{it-1}, k_{it-1}), k_{it-1})$ so that we may write k_{it} as a function of m_{it-1} and k_{it-1}, i.e., $k_{it}(m_{it-1}, k_{it-1})$ in the second line of (20). We estimate the survival probability (20) using a probit with third order polynomials in (m_{it-1}, k_{it-1}). Given $\omega^*_{t-1}(m_{it-1}, k_{it-1})$, we may invert (20) with respect to $\underline{\omega}_t$; therefore, we may write $\underline{\omega}_t$ as a function of survival probabilities, P^{χ}_{it}, and $\omega^*_{t-1}(m_{it-1}, k_{it-1})$ as in $\underline{\omega}_t(P^{\chi}_{it}, \omega^*_{t-1}(m_{it-1}, k_{it-1}))$.

Then, we may express $g_t(\underline{\omega}_t(k_{it}), \omega_{it-1})$ in (19) as a (year-specific) nonlinear function of $(P^{\chi}_{it}, \omega^*_{t-1}(m_{it-1}, k_{it-1}))$ as

$$\begin{aligned} & g_t(\underline{\omega}_t(P^{\chi}_{it}, \omega^*_{t-1}(m_{it-1}, k_{it-1})), \omega^*_{t-1}(m_{it-1}, k_{it-1})) \\ & \quad = \alpha_{0,t} + \int_{\underline{\omega}_t(P^{\chi}_{it}, \omega^*_{t-1}(m_{it-1}, k_{it-1}))}^{\infty} \omega_{it} \frac{F(d\omega_{it}|\omega^*_{t-1}(m_{it-1}, k_{it-1}))}{\int_{\underline{\omega}_t(P^{\chi}_{it}, \omega^*_{t-1}(m_{it-1}, k_{it-1}))}^{\infty} F(d\omega_{it}|\omega^*_{t-1}(m_{it-1}, k_{it-1}))}. \end{aligned}$$

Define

$$q_t(P^{\chi}_t, \alpha_{0,t-1} + \omega^*_{t-1}(m_{it-1}, k_{it-1})) \equiv g_t(\underline{\omega}_t(P^{\chi}_{it}, \omega^*_{t-1}(m_{it-1}, k_{it-1})), \omega^*_{t-1}(m_{it-1}, k_{it-1})),$$

and substituting this equation into (19) and using $\alpha_{0,t-1} + \omega^*_{t-1}(m_{it-1}, k_{it-1}) = \phi_{t-1}(m_{it-1}, k_{it-1}) -$

$\alpha_k k_{it-1} - \alpha_m m_{it-1}$, we have

$$x_{it} = \alpha_k k_{it} + \alpha_m m_{it} + q_t(P_t^{\chi}, h_{it-1}) + \xi_{it} + \epsilon_{it}, \tag{21}$$

where $h_{it} = \phi_t(m_{it}, k_{it}) - \alpha_k k_{it} - \alpha_m m_{it}$. This equation corresponds to equation (12) in OP.

Given the above definitions, we recover α_k and α_m in three distinct steps. First, let $\hat{x}_{it} = y_{it} - \{\hat{\alpha}_p l^u_{p,it} + \hat{\beta}_p x_{p,it} + \hat{\alpha}_n l^u_{n,it} + \hat{\beta}_n x_{n,it}\}$, where $(\hat{\alpha}_p, \hat{\alpha}_n, \hat{\beta}_p, \hat{\beta}_n)$ is the first stage estimate of corresponding parameters. Then we estimate $\phi(m_{it}, k_{it})$ by regressing $\hat{x}_{it}$ on third order polynomials in (m_{it}, k_{it}). Second, we estimate the survival probability by estimating the probit of survival ($\chi_{it} = 1$) conditional on (m_{it-1}, k_{it-1}) using third order polynomials. Third, for each candidate value of (α_k, α_m), we compute $\hat{h}_{it}(\alpha_k, \alpha_m) = \hat{\phi}_{it} - \alpha_k k_{it} - \alpha_m m_{it}$ and regress $\hat{x}_{it} - \{\alpha_k k_{it} + \alpha_m m_{it}\}$ on third order polynomials in $(\hat{P}^{\chi}_{it}, \hat{h}_{it-1})$ to obtain the estimate of $q_t(P^{\chi}_{it}, h_{it-1})$ as its predicted value, denoted by $\hat{q}_{it}(\alpha_k, \alpha_m)$. Denoting $(\widehat{\xi_{it} + \epsilon_{it}})(\alpha_k, \alpha_m) = \hat{x}_{it} - \{\alpha_k k_{it} + \alpha_m m_{it} - \hat{q}_{it}(\alpha_k, \alpha_m)\}$, we estimate (α_k, α_m) using the moment conditions $E[(\xi_{it} + \epsilon_{it}) m_{it-1}] = 0$ and $E[(\xi_{it} + \epsilon_{it}) k_{it-1}] = 0$. Note that we do not use k_{it} as an instrument because k_{it} will be correlated with ξ_{it} given that we take a long difference.

We apply the above estimation procedure to the two years of data from 1996 and 2006 so that the time subscripts $t-1$ and t correspond to 1996 and 2006, respectively. The Hicks-neutral productivity, including both the unexpected shock ϵ_{it} and the year-specific constant $\alpha_{0,t}$, is computed as

$$\varphi_{it} \equiv \alpha_{0,t} + \omega_{it} + \epsilon_{it} = y_{it} - (\hat{\alpha}_k k_{it} + \hat{\alpha}_m m_{it} + \hat{\alpha}_p l^u_{p,it} + \hat{\beta}_p x_{p,it} + \hat{\alpha}_n l^u_{n,it} + \hat{\beta}_n x_{n,it}).$$

We find that $(\alpha_k, \alpha_m, \alpha_p, \alpha_n, \beta_p, \beta_n)$ is estimated as $(0.017, 0.602, 0.152, 0.110, -0.253, -0.138)$. Note the production function parameters are very similar to those estimated elsewhere (e.g. See Amiti and Konings (2007)). Our estimates further imply that the elasticity of substitution parameters among production and non-production workers (σ_p, σ_n) are estimated to be (1.664,1.255).

As an alternative measure of productivity, we also estimate the "conventional" measure of total factor productivity (TFP) under the assumption that skilled and unskilled workers are perfect substitutes with a Cobb-Douglas production function given by

$$Y_{it} = e^{\varepsilon_{it}} Q_{it}, \quad \text{where} \quad Q_{it} = e^{\alpha_0 + \omega_{it}} K_{it}^{\alpha_k} M_{it}^{\alpha_m} \tilde{L}_{p,it}^{\alpha_p} \tilde{L}_{n,it}^{\alpha_n} \tag{22}$$

where $\tilde{L}_{p,it} = L^s_{p,it} + L^u_{p,it}$ and $\tilde{L}_{n,it} = L^s_{n,it} + L^u_{n,it}$. Repeating our estimation exercise under this restriction we again recover the parameters $(\alpha_k, \alpha_m, \alpha_p, \alpha_n)$ as $(0.030, 0.908, 0.065, 0.074)$. We also use this alternative structure and estimates to construct a second measure of productivity. In the main text this second measure is denoted as "conventional" TFP.

D Additional Tables

Table D.1: Definitions of the Variables

Variable	Definition
S	The log of the ratio of skilled workers to unskilled workers in 2006 in occupation $j \in \{p, n\}$, $\ln\left(\frac{L_s^j}{L_u^j}\right)_{06}$, the wage share of skilled workers in the total wage bill in 2006 in occupation $j \in \{p, n\}$, $\left(\frac{W_s L_s^j}{W_s L_s^j + W_u L_u^j}\right)_{06}$, or the log of the ratio of non-production workers to production workers in 2006, $\ln\left(\frac{L_s^n + L_u^n}{L_s^p + L_u^p}\right)_{06}$.
D	Equal to one if plant imports materials from abroad in 2006; zero otherwise.
X	Export dummy, capital stock, a measure of Hicks-neutral productivity, foreign ownership dummy, a dummy for positive R&D expenditures, a dummy for positive training expenditures, the log of the ratio of skilled workers' wages to unskilled workers' wages in the region where a plant locates, the 1996 value of the outcome variables denoted by $\ln\left(\frac{L_s^j}{L_u^j}\right)_{96}$, $\left(\frac{W_s L_s^j}{W_s L_s^j + W_u L_u^j}\right)_{96}$, and $\ln\left(\frac{L_s^n + L_u^n}{L_s^p + L_u^p}\right)_{96}$ for $j \in \{p, n\}$, a dummy for no hiring of skilled workers or unskilled workers in occupation $j \in \{p, n\}$ in 1996 denoted by $d_{s,96}^j := 1(L_s^j = 0)$ or $d_{u,96}^j := 1(L_u^j = 0)$, respectively, TFP measure constructed by the Levinsohn and Petrin method under the assumption of a Cobb-Douglas production function, 3-digit ISIC industry dummies, and province dummies.
$Z \backslash X$	Transport cost to the nearest port, a change in output and input tariff rates at 5-digit ISIC level between 1996 and 2001, interaction terms between transport cost and tariffs.

Notes: A skilled worker is defined as a worker with high school eduction and unskilled worker is defined as a worker without high school education. Occupation categories "p" and "n" denote production workers and non-production workers, respectively. All variables are measured in 2006 unless stated otherwise.

Table D.2: Descriptive Statistics for Variables for the Sample of Initial Non-Importers

	$D=0$		$D=1$	
Explanatory Variable[(a)]	Mean	S.D.	Mean	S.D.
TC	0.79	0.72	0.65	0.80
$\Delta\tau_y$	-6.76	9.61	-8.03	5.63
$\Delta\tau_m$	-3.39	6.90	-4.65	3.15
Export	0.15	0.36	0.39	0.49
Capital	13.28	1.83	14.56	2.32
φ	5.17	0.57	5.48	0.64
TFP	1.28	0.65	1.26	0.65
Foreign	0.01	0.11	0.08	0.27
R&D	0.05	0.21	0.14	0.35
Training	0.27	0.45	0.52	0.50
$\ln(W_s/W_u)$	0.61	0.16	0.59	0.14
$\ln(L_s^p/L_u^p)_{96}$	-0.73	1.33	-0.33	1.40
$d_{u,96}^p$	0.01	0.12	0.05	0.21
$d_{s,96}^p$	0.39	0.49	0.27	0.45
Standard	0.15	0.36	0.39	0.49
No. of Obs.	4342		306	

	$D=0$		$D=1$	
Outcome Variable[(b)]	Mean	S.D.	Mean	S.D.
$\ln(L_s^p/L_u^p)_{06}$	-0.53	1.65	0.12	1.80
$\ln(L_s^n/L_u^n)_{06}$	0.58	1.31	1.21	1.39
$\ln((L_u^n+L_s^n)/(L_u^n+L_s^n+L_u^p+L_s^p))_{06}$	-2.14	1.24	-2.05	1.36
$\ln(W_sL_s^p/(W_sL_s^p+W_uL_u^p))_{06}$	0.41	0.35	0.55	0.36
$\ln(W_sL_s^n/(W_sL_s^n+W_uL_u^n))_{06}$	0.66	0.42	0.69	0.41

Notes: (a) The sample statistics for the explanatory variables that are used to estimate the decisions to import reported in the column of "Initial Non-Importers" of Table 8. (b) The sample statistics for the outcome variables that are used to estimate the skill demand equation (10). In each case, the outcome variable is computed using the sample of initial non-importers.

Table D.3: The First Stage Regression using Linear Probability Model

Sample	Full Sample			Sample of Initial Non-importers ($D_{96}=0$)								
Dep. Var.	Import Dummy			Import Dummy				Export Dummy		Dummy for Standards		
Table-Column for 2nd Stage	Table 2-(2)	Table 2-(3)	Table 2-(4)	Table 2-(6)	Table 2-(7)	Table 2-(8)	Table 3-(4)	Table 3-(4)	Table 7-(2)	Table 6-(1)	Table 6-(2)	Table 6-(3)
d_{TC}	0.0900***			0.0472***						0.0804***		
	[0.013]			[0.011]						[0.019]		
TC		-0.0854***	-0.0869***		-0.0382***	-0.0341***	-0.0272**	0.0116	0.0200		-0.0665***	-0.0538***
		[0.011]	[0.012]		[0.009]	[0.011]	[0.012]	[0.013]	[0.013]		[0.016]	[0.017]
$\Delta\tau_y$			0.0030			0.0002	-0.0001	-0.0032**	-0.0032**			0.0020
			[0.002]			[0.002]	[0.002]	[0.002]	[0.002]			[0.003]
$\Delta\tau_m$			-0.0032			0.0007	-0.0006	0.0030	0.0015			-0.0054
			[0.003]			[0.002]	[0.002]	[0.002]	[0.002]			[0.004]
$\Delta\tau_y \times TC$			-0.0020			0.0010	0.0009	0.0019	0.0019			-0.0011
			[0.001]			[0.001]	[0.001]	[0.002]	[0.002]			[0.002]
$\Delta\tau_m \times TC$			0.0031			-0.0013	-0.0012	-0.0036	-0.0034			0.0021
			[0.002]			[0.001]	[0.002]	[0.002]	[0.002]			[0.003]
Export	0.1617***	0.1634***	0.1775***	0.0723***	0.0720***	0.0795***						
	[0.016]	[0.016]	[0.017]	[0.014]	[0.014]	[0.016]						
Capital	0.0211***	0.0211***	0.0213***	0.0088***	0.0093***	0.0087***	0.0097***	0.0250***	0.0193***	0.0272***	0.0272***	0.0291***
	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]
Hicks-neutral φ	0.0270***	0.0281***	0.0309***	0.0133	0.0133	0.0156*	0.0124	0.0288**	0.0323***	0.0344**	0.0350**	0.0305**
	[0.010]	[0.010]	[0.011]	[0.008]	[0.008]	[0.009]	[0.009]	[0.011]	[0.012]	[0.014]	[0.014]	[0.015]
Foreign	0.1892***	0.1885***	0.1856***	0.1196***	0.1168***	0.1038**	0.0824	0.1538**	0.1016	0.1114	0.1124	0.0417
	[0.035]	[0.035]	[0.038]	[0.045]	[0.045]	[0.050]	[0.063]	[0.071]	[0.077]	[0.087]	[0.088]	[0.094]
R&D	0.0693***	0.0705***	0.0631***	0.0751***	0.0725***	0.0530**	0.0526*	0.0621*	0.0598	0.1453***	0.1497***	0.1483***
	[0.022]	[0.022]	[0.024]	[0.024]	[0.024]	[0.026]	[0.030]	[0.036]	[0.037]	[0.045]	[0.045]	[0.048]
Training	0.0406***	0.0450***	0.0440***	0.0293***	0.0317***	0.0316***	0.0317***	0.0681***	0.0616***	0.1088***	0.1069***	0.1130***
	[0.012]	[0.012]	[0.013]	[0.010]	[0.010]	[0.011]	[0.012]	[0.015]	[0.014]	[0.018]	[0.018]	[0.019]
$\ln(\frac{W_s}{W_u})$	-0.0032	0.0148	0.0180	-0.0037	0.0069	0.0150	0.0335**	0.0227	0.0197	0.0290	0.0435	0.0467
	[0.018]	[0.018]	[0.020]	[0.013]	[0.014]	[0.014]	[0.016]	[0.023]	[0.023]	[0.030]	[0.030]	[0.031]
$\ln(\frac{L_s^p}{L_u^p})_{96}$	0.0105**	0.0113**	0.0117**	0.0070*	0.0077*	0.0063	0.0064	0.0047	0.0028	0.0111*	0.0103	0.0056
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.007]	[0.007]	[0.007]
$d_{u,96}^p$	0.0635	0.0664	0.0726	0.0650	0.0705	0.0671	0.0832	0.0116	-0.0178	-0.0263	-0.0234	0.0151
	[0.042]	[0.042]	[0.045]	[0.044]	[0.044]	[0.047]	[0.056]	[0.052]	[0.043]	[0.062]	[0.062]	[0.074]
$d_{s,96}^p$	-0.0268**	-0.0264*	-0.0173	0.0110	0.0107	0.0221*	0.0182	-0.0123	-0.0107	-0.0310*	-0.0306*	-0.0207
	[0.013]	[0.014]	[0.014]	[0.011]	[0.012]	[0.012]	[0.013]	[0.014]	[0.014]	[0.018]	[0.018]	[0.019]
No. Obs.	4,970	4,914	4,301	3,767	3,718	3,281	2,654	2,654	2,490	2,718	2,692	2,412
R-squared	0.238	0.242	0.244	0.119	0.120	0.111	0.092	0.189	0.174	0.230	0.228	0.246

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in parentheses. Province dummies and 3-digit ISIC industry dummies are also included.

Table D.4: Robustness Check: Skill Demand Equation for Production Workers using Full Sample

	Dependent Variable: $\ln(L_s^p/L_u^p)_{06}$					
	(1) Sample of $\text{Export}_{96}=0$ and $\text{Export}_{06}=0$; IV Import using d_{TC}	(2) Sample of $\text{Export}_{96}=0$ and $\text{Export}_{06}=0$; IV Import using TC	(3) Sample of $\text{Export}_{96}=0$ and $\text{Export}_{06}=0$; IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	(4) Sample of $\text{Export}_{96}=0$; IV both Import and Export using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	(5) Replace φ with TFP; IV Import using TC	(6) Replace φ with TFP; IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$
Import	1.8970**	2.4907***	3.0461***	3.2374***	2.3008***	2.2781***
	[0.739]	[0.847]	[0.994]	[0.953]	[0.570]	[0.608]
Export				0.7187	-0.3652***	-0.3398***
				[1.932]	[0.113]	[0.127]
TFP					0.0561	0.0625
					[0.037]	[0.041]
No. Obs.	3,267	3,239	2,881	3,229	4,916	4,303

	Dependent Variable: $\left(\frac{W_s L_s^p}{W_s L_s^p + W_u L_u^p}\right)_{06}$						
	(7) OLS	(8) IV Import using d_{TC}	(9) IV Import using TC	(10) IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	(11) Sample of $\text{Export}_{06}=0$ and $\text{Export}_{96}=0$ IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	(12) Sample of $\text{Export}_{96}=0$ IV both Import and Export using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$	(13) Replace φ with TFP; IV Import using $(TC,\, \Delta\tau_m,\, \Delta\tau_y)$
Import	0.0324***	0.5501***	0.4745***	0.4223***	0.5144***	0.4540**	0.4055***
	[0.009]	[0.113]	[0.101]	[0.111]	[0.176]	[0.181]	[0.108]
Export	0.0255***	-0.0626***	-0.0491**	-0.0387*		-0.3454	-0.0378*
	[0.009]	[0.022]	[0.021]	[0.023]		[0.428]	[0.023]
TFP							0.0155**
							[0.007]
No. Obs.	7,123	7,123	7,051	6,192	4,530	4,951	6,194

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in parentheses. Columns (1)-(13) use the same set of explanatory variables as in Table 2 except that we use the "conventional" TFP measure based on Cobb-Douglas production function in place of Hicks-neutral productivity measure ϕ in columns (5), (6), and (13) while we include $\left(\frac{W_s L_s^p}{W_s L_s^p + W_u L_u^p}\right)_{96}$ in place of $\ln(\frac{L_s^p}{L_u^p})_{96}$, $d_{u,96}^p$, and $d_{s,96}^p$ in columns (7)-(13). The full sample is used except in columns (1)-(3) and (11) where we use the subsample of plants that do not export in 2006 while columns (4) and (12) use the subsample of plants that do not export in 1996 or in 2006.

Table D.5: Skill Demand, Export Decision, and Initial Skill Levels using Sample of Plants that Neither Import Nor Export in 1996 (D_{96} =Export$_{96}$ = 0)

	Dep. Var.: $\ln(L^p_s/L^p_u)_{06}$			Dep. Var.: Export Dummy in 2006		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Export$_{96}$ = 0 $D_{96} = 0$ $D_{06} = 0$	Export$_{96}$ = 0 $D_{96} = 0$ $D_{06} = 0$	Export$_{96}$ = 0 $D_{96} = 0$	Export$_{96}$ = 0 $D_{96} = 0$	Export$_{96}$ = 0 $D_{96} = 0$ $D_{06} = 0$	Export$_{96}$ = 0 $D_{96} = 0$
IV or OLS	IV Export using ($\Delta\tau_m$, $\Delta\tau_y$)	IV Export using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	IV both Import and Export using (TC, $\Delta\tau_m$, $\Delta\tau_y$)	OLS	OLS	IV Import using TC
Import			5.1904*	0.1263***		-0.4408
			[2.656]	[0.030]		[0.501]
Export	1.4183	-0.9551	-1.0712			
	[1.471]	[1.218]	[1.855]			
TC				0.0151	0.0200	
				[0.013]	[0.013]	
$\Delta\tau_y$				-0.0032**	-0.0032**	-0.0018
				[0.002]	[0.002]	[0.001]
$\Delta\tau_m$				0.0031	0.0015	-0.0014
				[0.002]	[0.002]	[0.002]
$\Delta\tau_y \times TC$				0.0018	0.0019	
				[0.002]	[0.002]	
$\Delta\tau_m \times TC$				-0.0035	-0.0034	
				[0.002]	[0.002]	
Capital	0.1253***	0.1676***	0.1335**	0.0238***	0.0193***	0.0292***
	[0.036]	[0.033]	[0.053]	[0.004]	[0.004]	[0.006]
Hicks-neutral φ	-0.3224***	-0.2506***	-0.3099***	0.0272**	0.0323***	0.0343**
	[0.071]	[0.069]	[0.088]	[0.012]	[0.012]	[0.014]
Foreign	-0.0253	0.2204	-0.1748	0.1434**	0.1016	0.1913**
	[0.292]	[0.313]	[0.513]	[0.070]	[0.077]	[0.092]
R&D	0.0391	0.1843	-0.0887	0.0554	0.0598	0.0880*
	[0.156]	[0.152]	[0.253]	[0.036]	[0.037]	[0.048]
Training	0.1311	0.2772***	0.1537	0.0641***	0.0616***	0.0815***
	[0.117]	[0.106]	[0.164]	[0.014]	[0.014]	[0.022]
$\ln(\frac{W_s}{W_u})$	0.0826	0.1248	0.0097	0.0185	0.0197	0.0380
	[0.112]	[0.105]	[0.142]	[0.023]	[0.023]	[0.026]
$\ln(\frac{L^p_s}{L^p_u})_{96}$	0.3732***	0.3796***	0.3377***	0.0039	0.0028	0.0075
	[0.026]	[0.026]	[0.039]	[0.005]	[0.005]	[0.007]
$d^p_{u,96}$	0.3596	0.3125	-0.0637	0.0011	-0.0178	0.0483
	[0.296]	[0.299]	[0.437]	[0.050]	[0.043]	[0.075]
$d^p_{s,96}$	-0.9668***	-1.0094***	-1.1348***	-0.0146	-0.0107	-0.0058
	[0.080]	[0.080]	[0.110]	[0.014]	[0.014]	[0.018]
No. Obs.	2,510	2,490	2,654	2,654	2,490	2,654
R-squared				0.199	0.174	

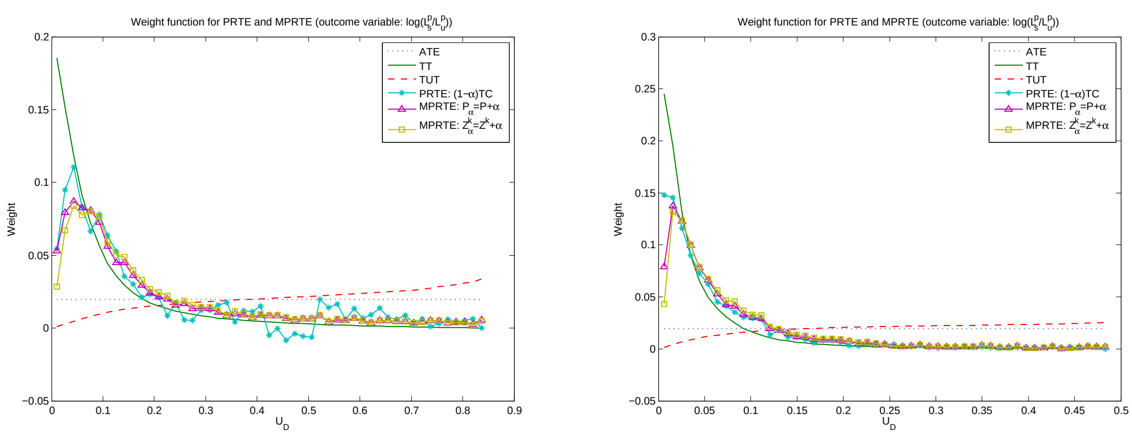
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard deviations are in parentheses. Province dummies and 3-digit ISIC industry dummies are also included. This table reports full specifications and their estimates of Table 7.

Table D.6: Treatment Effects of Importing on Skill Demand using the Ratio of Non-Production Workers to Production Workers using the Sample of Initial Non-Importers

Dep. Var.	$\ln\left(\frac{L_u^n+L_s^n}{L_u^p+L_s^p}\right)_{06}$
ATE	0.3508
	[2.0258][(a)]
	(-0.7075,1.4927)[(b)]
TT	0.6594
	[1.5838]
	(-1.2319,3.0656)
TUT	0.3062
	[2.4386]
	(-0.6996,1.3492)
	[0.0051,0.4803]
MPRTE	0.6136
$(P_\alpha^* = P + \alpha)$	[1.3339]
	(-1.0758,2.7724)
MPRTE	0.6016
$(Z_\alpha^{k*} = Z^k + \alpha)$	[1.2866]
	(-1.0668,2.6922)
PRTE	0.6189
$(TC^* = 0.99TC)$	[1.3438]
	(-1.1037,2.8036)
Support[(c)]	[0.007,0.842]
No. of Obs.[(d)]	4281

Notes: (a) The bootstrap standard errors are in square brackets. (b) The bootstrap equal-tailed 90 percent confidence intervals are in parentheses. (c) The minimum and the maximum values of support over which treatment effects are computed; various treatment effects are computed by restricting the weights to integrate to one on the restricted support, for which minimum and maximum values are determined by the 1^{st} percentile and the 99^{th} percentile of observations in the common support, respectively. (d) The sample size for estimating the MTE curve.

Figure D.1: Weights for ATE, TT, TUT, MPRTEs, and PRTE (Dependent Variables: $\ln(L_s^p/L_u^p)$)



(a) Production Workers, Full Sample

(b) Production Workers, Initial Non-Importers

Figure D.2: Estimated MTE for Dependent Variable $\ln\left(\frac{L_u^n+L_s^n}{L_u^p+L_s^p}\right)_{06}$ using the Sample of Initial Non-Importers