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* and *across* production and non-production occupations 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. Both instrumental variable regression and marginal treatment effect estimates confirm that importing has substantially increased the relative demand for educated workers within each occupation. In contrast, we do not consistently estimate a significant impact of importing on the relative demand for 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 plant-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)). 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).[1]

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 between 1996 and 2006. 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, inducing skill-biased technological change (SBTC, hereafter).[2] 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

[1]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), studies of 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 studies of 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; Parro, 2013).

[2]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 (2015), 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.

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 *within* and *across* occupations to observable decisions to import intermediate materials at the plant-level.

Our data are exceptionally well suited to this objective. Typically, researchers have used 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).[3] Likewise, Amiti and Cameron (2012) investigate the impact of trade liberalization on the wages of production workers relative to non-production workers. They find that falling input tariffs has caused the wage of non-production workers to fall relative to the wage of production workers within Indonesian manufacturing firms that import their intermediate inputs. A major advantage of this paper's study is that it is able to capture a much more precise measure of skill at the plant-level in a large, developing economy. Specifically, our 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.

In the last two decades, Indonesia has experienced a large increase in the supply of educated workers. In fact, using the balanced panel of manufacturing plants, we find that the plant-level average share of educated workers—defined as the workers with a highschool diploma—increased by 14.5 percentage points between 1996 and 2006. When we decompose the overall increase in the share of educated workers into the increase *within* occupation categories and the increase due to reallocation *between* occupation

[3] Important exceptions are Bustos (2011) and Koren and Csillag (2011). 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, a number of studies use linked data firm and employee data to establish a number of related findings. In particular, Frazer (2013) examines the effect of importing on Rwandan manufacturing wages, Hummels (2014) characterizes the relationship between offshoring and wages across skilled and unskilled Danish workers, Martins and Opromolla (2009) investigates the impact of importing on Portugese manufacturing wages, while Krishna et al (2011) and Menezes-Filho and Muendler (2011) study how trade reform affects Brazilian wages and worker displacement, respectively. Ebenstein et al (2014) examine the impact of offspring on US wages using CPS. While these studies offer insight into the effect of importing on the workers' wages or displacement, we examine the effect of importing on the relative employment of educated workers to less educated workers at the plant-level.

categories, we find that the skill upgrading within production and within non-production workers account for more than 95 percent of the overall increase in the share of educated workers; the reallocation from production to non-production workers account for less than 5 percent. Since little of the skill-upgrading at the plant-level can be explained by the reallocation of workers across occupations, existing studies that focus on the relative demand for non-production workers to production workers provide limited insight on how importing affects the overall demand for educated workers. This paper contributes to the literature by investigating the impact of importing on the demand for educated workers within occupation categories.

Quantifying the impact of importing on the demand for educated workers 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 develop a number of detailed instruments to capture exogenous variation in plant-level import shipping costs. We exploit this variation to identify robust IV estimates of the causal impact of importing on the demand for skilled labour. Our IV results consistently indicate that most within-firm education-based skill-upgrading occurs *within* occupations. Moreover, traditional measures of skill upgrading in existing studies, such as the fraction of non-production workers, tend to understate the degree of skill upgrading induced by importing.

Second, we are also concerned that the unobservable impact of trade on the demand for educated workers 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 because these plants gain more from importing. This "selection on gains" complicates estimation in general, and even a standard first differenced estimator is invalid as an estimator for the average treatment effect because this source of the bias cannot be differenced out.

By applying the treatment effect framework developed by Heckman and Vytlacil (2005, 2007a, 2007b), we estimate the Marginal Treatment Effect (MTE, hereafter) curve as well as various summary measures of the impact of importing on the relative demand 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).

The estimated MTE curve is well above zero and downward sloping, where the latter feature provides direct evidence that the impact of importing on the demand for educated workers varies across plants (i.e., the coefficient is random) and plants that receive a larger idiosyncratic gain from importing are more likely to start importing. The estimates of the ATE, the TT, and the TUT of importing on the demand for educated workers are significantly positive. Furthermore, the TT is consistently estimated to be substantially larger than the ATE, which, in turn, is estimated to be larger than the TUT. This suggests that, on average, the effect of importing among plants that have chosen to import is substantially larger than that among plants that have chosen not to import in our sample. These findings are not just of academic interest, but imply that while importing may have had an important impact on the demand for educated workers among plants that were induced to import in our sample, it is unclear that further policy change will greatly affect the demand for educated workers among new importers.

In the presence of heterogenous effects, the instrumental variable (IV) estimator identifies the Local Average Treatment Effect (LATE), which is the average effect of importing among plants induced to change their import status by an instrument (Imbens and Angrist, 1994). However, the plants that are induced to start importing by an instrument may be different from the plants that would have been induced to start importing by a policy change. We use the framework of Carneiro, Heckman, and Vytlacil (2010) to study the average impact of further policy changes on the demand for educated workers among the set of plants induced to import by the change in policy. The results suggest that further policy changes that promote importing would have increased the demand for educated workers among the plants induced to start importing, but these changes are smaller than that implied by the TT or our IV estimates.

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

2 A Simple Model of Importing, Selection and SBTC

Consider a simple two-country model of importing where home (Indonesian) firms consider whether or not to import from abroad. Consumers have CES preferences and the market structure is monopolistic competition. A home firm producing variety ω faces home demand $q(\omega) = B(Z_d)p(\omega)^{-\eta}$ where q is quantity demanded, p is the output price, η is the elasticity of substitution, and Z_d is a vector of observed variables that serve as a demand shifter.[4]

Firms hire capital, skilled labor, and unskilled labor on competitive factor markets and combine them with intermediate materials - purchased domestically or imported - to produce output according to the production function

$$f(K, M, L_s, L_u, A, \varphi) = \varphi K^{\alpha_k} M^{\alpha_m} \{[AL_s]^{(\sigma-1)/\sigma} + L_u^{(\sigma-1)/\sigma}\}^{\alpha_l \sigma/(\sigma-1)}, \tag{1}$$

where K is capital, M is total intermediate materials, 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 notational simplicity we abstract from differences across occupations, though allowing differences across production and non-production workers is straightforward.

To consider the potential impact of importing on the relative demand for skilled workers, we allow foreign imported inputs to affect the level of skilled labor augmenting technology as

$$\ln A(X, D, \tilde{\beta}) = D\tilde{\beta} + X\tilde{\gamma}' + \tilde{U}, \tag{2}$$

where D is a dummy variable for the use of imported inputs, $\tilde{\beta}$ is a firm-specific parameter that captures the effect of importing on skill-biased technology A, X is a vector of observables (to be specified later), and $\tilde{U}$ is a skill-biased technology shock. The skill biased technology term A depends on X and the import decision D as in (2) but we assume that importing does not affect the Hicks neutral technology level φ.[5]

For simplicity, we assume constant returns to scale technology where the plant's marginal cost is determined by

$$c(A, \varphi) = \min_{L_s, L_u, K, M} W_s L_s + W_u L_u + W_k K + W_m M \text{ subject to } f(L_s, L_u, K, M, A, \varphi) \geq 1 \tag{3}$$

[4]We abstract from the possibility of exporting for the moment, though it will be straightforward to extend our framework to allow for it. We can also directly extend the model to allow for unobserved demand/cost shifters.

[5]It is also possible to allow importing to improve Hicks-Neutral productivity or product quality. We abstract from the former possibility only for expositional simplicity, while the latter consideration leads to a similar estimating equation. Although we investigate different mechanisms which drive skill upgrading through imports, import-induced skill-biased technological change may operate through either productivity or product quality.

and (W_s, W_u, W_k, W_m) is a vector of factor prices. If the plant chooses to import, it incurs a fixed import cost $f_m(Z_c)$ where Z_c contains a vector of observed variables that determine the fixed cost. Then the plant's net profit function is $\pi(A, Z_d, Z_c, \varphi, D) = r(A, Z_d, \varphi) - Df_m(Z_c)$, where $r(A, Z_d, \varphi) = \max_q pq - c(A, \varphi)q$. A firm will import whenever the net profit from importing is greater than the net profit achieved using domestic materials alone,

$$\Delta\pi(X, Z_d, Z_c, \varphi, \tilde{\beta}) := \pi(A(X, 1, \tilde{\beta}), Z_d, Z_c, \varphi, 1) - \pi(A(X, 0, \tilde{\beta}), Z_d, Z_c, \varphi, 0) \geq 0. \quad (4)$$

Note that $\Delta\pi(X, Z_d, Z_c, \varphi, \tilde{\beta})$ is strictly increasing in $\tilde{\beta}$ and φ.

Suppose we allow $\tilde{\beta}$ to vary across plants as

$$\tilde{\beta} = \bar{\tilde{\beta}} + \tilde{\epsilon},$$

where $\bar{\tilde{\beta}}$ is the mean of $\tilde{\beta}$ and $\tilde{\epsilon}$ is the plant-specific return to importing. Then, for each value of X, Z_d, Z_c, and φ, it is straightforward to determine a threshold value of $\tilde{\beta}$ that induces firms to start importing by the condition $\Delta\pi(X, Z_d, Z_c, \varphi, \tilde{\beta}^*) = 0$. This threshold value $\tilde{\beta}^*$ depends on X, Z_d, Z_c, and φ. Naturally, firms with low initial productivity φ will require larger values of $\tilde{\beta}$ to justify importing.[6]

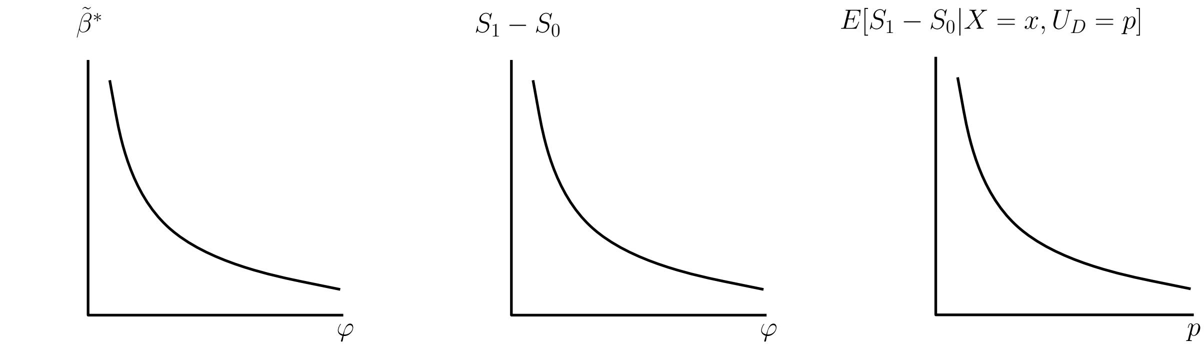
Under the assumption of heterogeneous returns to importing, we can illustrate the selection mechanism by considering the locus of $\tilde{\beta}$'s for the marginal importer. Figure 1(a) demonstrates that this locus is strictly decreasing in initial Hicks-neutral productivity, φ, while fixing the value of X, Z_d, and Z_c. Firms with low Hicks-neutral productivity (i.e., low value of φ) choose to import only if they receive high idiosyncratic returns from importing (i.e., high value of $\tilde{\beta}$).

2.1 Selection, SBTC and Skill Demand

Consider the first order conditions from cost minimization problem (3). Denote the log of the demand for skilled workers relative to unskilled workers by $S_D = \ln(L_s/L_u)$ for $D \in \{0, 1\}$, where the subscript D indicates its dependence on import status. Given market wages, the relative demand for skilled workers is determined by equating the ratio

[6] This argument is analogous to that in Lileeva and Trefler (2010) which studies the heterogeneous return to exporting on Hicks-neutral productivity.

Figure 1: Importing and Skill Demand



(a) Marginal Importer's $\tilde{\beta}^*$ (b) Marg. Importer's $S_1 - S_0$ (c) MTE

of the marginal product of skilled and unskilled workers to the ratio of their wages as

$$\begin{aligned} S_D &= (\sigma - 1)\ln A - \sigma \ln(W_s/W_u) \\ &= D\beta + X\gamma' + U \\ &= D(\bar{\beta} + \epsilon) + X\gamma' + U, \end{aligned} \tag{5}$$

where (β, $\bar{\beta}$, ϵ, γ, U) are ($\frac{\tilde{\beta}}{\sigma-1}$, $\frac{\bar{\tilde{\beta}}}{\sigma-1}$, $\frac{\tilde{\epsilon}}{\sigma-1}$, $\frac{\tilde{\gamma}}{\sigma-1}$, $\frac{\tilde{U}}{\sigma-1}$) and X subsumes $\ln(W_s/W_u)$. In our context, importing is an endogenous decision because the import decision D and skill-biased technology shock U are likely to be correlated. Moreover, as indicated in (4), plants with a greater ability to adopt skilled-biased technology (i.e., high value of β) will self-select into importing because they will achieve larger productivity gains from importing. Therefore, β and D are also correlated.

Because of this positive sorting on the gain from importing, we would expect that the change in skill demand will be greater among plants that choose to import relative to non-importers should they have started importing. As illustrated in Figure 1(b), and similar to Figure 1(a), the effect of importing on demand for skill for the marginal importer is a decreasing function of Hicks-neutral productivity φ.

2.2 The Marginal Treatment Effect

We are interested in identifying the impact of importing on the demand for skilled labor, β, which may vary across plants. 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 who are induced to change their import choices 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.

To evaluate the heterogeneous impact of importing on the demand for skill, we use the framework developed by Heckman and Vytlacil (1999, 2005, 2007a, 2007b) as follows. The relative demand for skilled labor S_D for $D = 0$ or 1 can be written as

$$S_1 = \mu_1(X) + U_1 \text{ and } S_0 = \mu_0(X) + U_0, \tag{6}$$

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

To derive an empirical specification for the decision to import, let $Z \equiv (X, Z_d, Z_c, \varphi)$ and write (4) as $\Delta\pi(Z, \tilde{\beta}) \equiv \Delta\pi(X, Z_d, Z_c, \varphi, \tilde{\beta})$. Define the latent variable, D^*, as $D^* = \Delta\pi(Z, \tilde{\beta}) = \mu_D(Z) - V$, where $\mu_D(Z) = E[\Delta\pi(Z, \tilde{\beta})|Z]$ is a deterministic function of observable variables Z while $V = \Delta\pi(Z, \tilde{\beta}) - \mu_D(Z)$ is a mean-zero unobserved stochastic component. Then, we have a latent variable model of importing:

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

A plant imports if $D^* \geq 0$; it does not import otherwise. We assume that the distribution of V, denoted by F_V, is continuous and strictly increasing and, furthermore, that (U_0, U_1, V) is statistically independent of Z given X and φ.[7]

Let $P(Z)$ denote the probability of importing conditional on Z so that $P(Z) \equiv \text{Prob}(\mu_D(Z) > V) = F_V(\mu_D(Z))$. $P(Z)$ is called the *propensity score*. Define $U_D \equiv F_V(V)$, and the random variable U_D is uniformly distributed on $[0, 1]$ by construction. Because V is the unobserved component of the net benefit of importing, U_D represents the quantiles of the unobserved net benefit from importing. Then the import decision (7) is alternatively written as $D = 1$ if $P(Z) \geq U_D$ and $D = 0$ otherwise.

[7] The latter is implied by the independence and monotonicity assumptions of Imbens and Angrist (1994) as shown by Vytlacil (2002).

We define the marginal treatment effect (MTE) as

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

This is the average effect of importing on skilled demand for plants with $X = x$ and $U_D = p$. Because a plant is indifferent between importing and not importing when $P(Z) = U_D$, the MTE captures the mean impact from importing on the demand for skilled labor among plants with $X = x$ and $P(Z) = p$ when the realization of U_D is such that the plant is just indifferent between importing and not importing.

Estimating the MTE for each value of $U_D = p$ within the support of $P(Z)$, we are able to construct the empirical counterpart to the locus of returns as outlined in Figure 1(c). Compared to Figures 1(a) or (b), the x-axis is measured in import probabilities rather than productivity in Figure 1(c) since we allow firms to differ in many dimensions rather than only productivity. Propensity scores are a natural metric to summarize those observed differences in a single dimension. When firms self-select into importing based on their unobserved benefits from importing, we expect the MTE curve to be downward sloping because, if firms choose to import even if their observed characteristics suggest that they were not likely to import (i.e., the low value of $P(Z) = p$), the unobserved component of net benefit from importing must be high (i.e., the high value of $E[U_1 - U_0|X = x, U_D = p]$ in (8)). In contrast, we expect the MTE curve to be flat in the absence of self-selection based on the unobserved benefit from importing.

Further, as described by Heckman and Vytlacil (2005, 2007a, 2007b), the MTE also 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. Details for each of these calculations can be found in Appendix B.

3 Data

3.1 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 and production) in each plant. Specifically, in each plant we observe the number of workers with primary, secondary and post-secondary education. We construct relative skill measures that are directly based on the workers' education levels for each occupation category.

The survey covers all manufacturing plants with at least 20 employees.[8] 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. It also includes plant-level input and output variables, such as total revenues, capital stock, domestic materials, and other 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.

To control for regional labor market conditions we augment the manufacturing survey with the Indonesian household survey.[9] The Indonesian household survey covers a nationally representative sample of households and documents key labor force information including gender, age, location, educational attainment and labor force experience. We use the household survey to develop a measure of the skill premium in each location and year.

3.2 Importing and Worker Education

3.2.1 Descriptive Statistics

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. In columns (8)-(10), "Training/Worker" and "R&D/Worker" report the average per worker expenditures on training

[8] A limitation of this paper is that in low-income countries a large share of firms have few employees (see McCaig and Pavcnik (2014, 2015) for examples). However, these are likely also firms that do not directly import or export and typically lack a skilled labor force.

[9] The manufacturing survey data do not provide a measure of wages by education level.

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.

Panel A of Table 1 also compiles similar statistics for exporting plants, non-exporting plants, and foreign-owned plants.[10] We observe a number of stark patterns: foreign plants tend to employ more educated 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 educated workers. The last row of Panel A documents the distribution of skilled labor for plants which did not import in 1996, where the reduction in sample size is driven by the fact that only a fraction of 2006 firms exist in 1996. The skill differences across firms which never import and those which start importing demonstrate very similar patterns to the full sample even though the sample is much smaller.

Panel B of Table 1 documents the percentage of workers in each educational category within production or non-production workers. For production workers, importing plants are found to systematically hire more workers with education levels above high school. While this remains true for non-production workers, it is much less stark. Instead, we observe that importing plants tend to hire a substantially greater share of college-educated non-production workers.

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 across occupation categories, we analyze the impact of importing on the demand for educated workers within the production occupation separately from that within the non-production occupation.

Among production workers, many Indonesian plants do not hire any workers with

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

college or post-graduate training. As a result, defining a skilled worker as a "college graduate" in our sample of production workers would eliminate a significant number of plants that are wholly composed of workers without college education. On the other hand, using a highschool education threshold would potentially obscure a key margin on which firms upgrade employee skill in response to importing among non-production workers because the difference in non-production hiring between importers and non-importers is clearest at college level, as documented in Table 1. For these reasons, we choose to define a skilled worker as one with at least a high school degree for production workers, and as one with at least a college degree for non-production workers.

3.2.2 Decomposing Changes in Plant-Level Skill Shares

To better characterize the development of the Indonesian labor market, we examine the importance of the reallocation of labor from the production to non-production occupation (a "between" component) relative to the education upgrading within each occupation (a "within" component). Specifically, we decompose the change in the overall share of educated workers for each plant as

$$\Delta \frac{L_s}{L} = \underbrace{\Delta \frac{L_s^p}{L^p} \times \overline{\frac{L^p}{L}}}_{\text{within prod.}} + \underbrace{\Delta \frac{L_s^n}{L^n} \times \overline{\frac{L^n}{L}}}_{\text{within non-prod.}} + \underbrace{\left(\overline{\frac{L_s^p}{L^p}} - \overline{\frac{L_s^n}{L^n}} \right) \times \Delta \frac{L^p}{L}}_{\text{between}}, \tag{9}$$

where $\Delta (L_s/L) = (L_s/(L_s + L_u))_{06} - (L_s/(L_s + L_u))_{96}$ is the change in the overall share of educated workers between 1996 and 2006, $\Delta (L_s^j/L^j) = (L_s^j/(L_s^j + L_u^j))_{06} - (L_s^j/(L_s^j + L_u^j))_{96}$ is the change in the share of educated workers within occupation j, $\Delta (L^p/L) = (L^p/(L^p + L^n))_{06} - (L^p/(L^p + L^n))_{96}$ is the change in the share of workers in the production occupation, and $\overline{(L^j/(L^p + L^n))} = \{(L^j/(L^p + L^n))_{96} + (L^j/(L^p + L^n))_{06}\}/2$ and $\overline{(L_s^j/(L_s^j + L_u^j))} = \{(L_s^j/(L_s^j + L_u^j))_{96} + (L_s^j/(L_s^j + L_u^j))_{06}\}/2$ are the average of the corresponding share variables. The superscripts "p" and "n" represent production and non-production occupations, while the subscript "s" and "u" represent skilled and unskilled workers, respectively. Likewise, the subscripts "96" and "06" indicate whether a variable is measured in 1996 or 2006.

Table 2 reports the average value of each of the three decomposition components across plants. In the second column, defining educated workers as those workers with a highschool diploma, the overall share of educated workers increased by 14.5 percentage points from 0.322 to 0.467 between 1996 and 2006, and this increase is mostly explained

Table 1: Importing and Skill Intensity 2006, full sample

Panel A: All Workers

	Highest Degree Completed/Fraction						Training	R&D	Non-Prod.	Obs.
	No Primary	Primary	Jr. High	High	College	Grad.	Worker	Worker	All Worker	
	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-Imp.	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-Imp.	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-Imp.	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-Imp.	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)	
	Initial Non-Importers									
Importers	0.038	0.114	0.273	0.503	0.072	0.0008	47.2	59.9	0.191	659
	(0.127)	(0.193)	(0.212)	(0.259)	(0.088)	(0.004)	(297.2)	(387.5)	(0.163)	
Non-Imp.	0.050	0.224	0.325	0.365	0.036	0.0002	16.6	14.7	0.154	7,465
	(0.134)	(0.280)	(0.244)	(0.283)	(0.064)	(0.003)	(241.9)	(212.7)	(0.159)	

Panel B: Production vs. Non-Production Workers

	Production Workers					Non-Production Workers				
	No Primary	Primary	Jr. High	High	College+	No Primary	Primary	Jr. High	High	College+
	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-Imp.	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-Imp.	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-Imp.	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-Imp.	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)
	Initial Non-Importers									
Importers	0.039	0.126	0.297	0.507	0.031	0.010	0.035	0.166	0.540	0.250
	(0.129)	(0.207)	(0.227)	(0.286)	(0.064)	(0.088)	(0.131)	(0.226)	(0.258)	(0.235)
Non-Imp.	0.052	0.243	0.348	0.343	0.014	0.011	0.056	0.201	0.570	0.162
	(0.141)	(0.298)	(0.264)	(0.305)	(0.047)	(0.082)	(0.181)	(0.277)	(0.320)	(0.229)

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 more than 90% of equity is held by domestic investors.

Table 2: A Decomposition of Plant-Level Skill Growth by Import Status

Def. of Skilled Workers	**Highschool+**			**College+**		
		Initial Non-importers			Initial Non-importers	
Sample	All	switchers	non-switchers	All	switchers	non-switchers
$\Delta(L_s/L)$	0.1446	0.1636	0.1425	0.0175	0.0270	0.0144
within prod.	0.1248	0.1409	0.1235	0.0058	0.0067	0.0048
within non-prod.	0.0137	0.0113	0.0128	0.0106	0.0147	0.0085
between	0.0060	0.0114	0.0062	0.0011	0.0056	0.0011
No. Obs	10,537	658	7,464	10,537	658	7,464

[a.] Source: Indonesia Manufacturing Survey in 1996 and 2006.
[b.] Skilled workers are defined as workers with education no less than highschool in the second to fourth columns and workers with no less than college in the fifth to last columns. Plants with no production workers in 1996 or 2006 are excluded (only three observations). Plants with no non-production worker in either period are treated as having zero within-non-production changes, and the mean value of skill share in non-production sector $\overline{(L_s^n/L^n)}$ is computed using the period when the number of non-production workers is positive. Plants with no non-production workers in both 1990 and 2006 simply have a zero within non-production component and zero between component.

by the skill upgrading within occupations.[11] In fact, skill upgrading within production workers and non-production workers, respectively account for 86 percent and 10 percent of the overall change in the share of skilled workers while the reallocation of workers from the production to non-production occupation contributes less than 5 percent. The third and fourth columns compare the plants that never imported ("non-switchers") with those that started importing ("switchers") and show that skill upgrading is higher at all margins for switchers except within non-production workers. The overall differences in skill share growth between switchers and non-switchers is largely driven by the differences in skill share growth within production workers.

The fifth to eighth columns repeat the same decomposition exercise, but define skilled workers as those workers with an educational attainment of no less than college. In the fifth column, the overall share of college educated workers increased by 1.75 percentage points from 0.325 to 0.500 between 1996 and 2006, and the "within non-production" term in the decomposition accounts for more than 60 percent of the change in the share of college educated workers. We similarly find that the differences in skill share growth within non-production workers is largest determinant of the difference between the college worker share growth across switchers and non-switchers.

[11] Table G.5 in Appendix reports details. Appealing to census data, we also find that there is similar growth in the supply of skilled (highschool or college) manufacturing workers.

Table 3: Definitions of the Variables

Var.	Definition
S	(1) The log of the ratio of skilled workers to unskilled workers in 2006 in occupation $j \in \{p, n\}$, $\ln\left(L_s^j/L_u^j\right)_{06}$, across both occupations, $\ln\left(L_s/L_u\right)_{06}$, or the log of the ratio of non-production workers to production workers in 2006, $\ln\left(L^n/L^p\right)_{06}$. (2) The fraction of skilled workers in 2006 in occupation $j \in \{p, n\}$, $\left(L_s^j/(L_s^j + L_u^j)\right)_{06}$, across both occupations (highschool or college), $\ln\left(L_s/L_u\right)_{06}$, and the fraction of non-production workers in 2006, $\left(L^n/(L^n + L^p)\right)_{06}$.
D	Equal to one if plant imports materials from abroad in 2006; zero otherwise.
X	Export dummy, capital stock, Hicks-neutral productivity, a 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 1996 and in 2006 in each region, local changes in the supply of skilled labor, the 1996 value of the outcome variables (denoted by replacing "06" with "96"), 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 $d_{u,96}^j := 1(L_u^j = 0)$, TFP constructed by the Levinsohn and Petrin method, 3-digit ISIC industry dummies, and province dummies.
$Z \backslash X$	Transport costs to the nearest port, the fraction of Indonesian imports shipped by air in industry j, the average weight of Indonesian imports in industry j, a change in output and input tariff rates at 5-digit ISIC level between 1996 and 2001.

Notes: A skilled worker is defined as a worker with high school eduction and an 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.

3.3 Variable Definitions

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 consists of plants that are present in both the 1996 and 2006 data sets. The definitions of variables and their descriptive statistics are reported in Tables 3 and 4.

We consider eight different outcome variables. Our first two measures, $\ln\left(L_s^p/L_u^p\right)_{06}$ and $\ln\left(L_s^n/L_u^n\right)_{06}$, directly capture the number of skilled workers within each occupation category in 2006, where L_s^j and L_u^j are the number of skilled workers and unskilled workers, respectively, employed in occupation $j \in \{p, n\}$. We define a skilled production worker as one with at least a highschool diploma and a skilled non-production worker as one with a college degree. A non-trivial number of plants that do not hire any skilled workers are dropped from our sample when we use the log of the ratio of skilled workers to unskilled workers as an outcome variable. Because this omission may generate selection bias, we also consider the outcome variables that measure the fraction of skilled workers' in each occupation category, denoted by $\left(L_s^p/(L_s^p + L_u^p)\right)_{06}$ and $\left(L_s^n/(L_s^n + L_u^n)\right)_{06}$. To examine the total relative demand for educated workers, the fifth and sixth outcome variables aggre-

Table 4: Descriptive Statistics

	$D=0$		$D=1$			$D=0$		$D=1$	
Explanatory Variable[(a)]	Mean	S.D.	Mean	S.D.	Explanatory Variable	Mean	S.D.	Mean	S.D.
TC	0.874	0.924	0.631	0.814	$\log(W_s/W_u)_{06}^{high}$	0.435	0.187	0.449	0.152
Air	0.087	0.068	0.114	0.090	$\log(W_s/W_u)_{06}^{coll}$	0.571	0.271	0.555	0.218
Export	0.175	0.380	0.434	0.497	$\log(W_s/W_u)_{96}^{high}$	0.472	0.146	0.459	0.140
Capital	13.570	1.808	15.086	2.034	$\log(W_s/W_u)_{06}^{coll}$	0.580	0.243	0.586	0.264
Hicks-neutral φ	5.229	0.582	5.538	0.636	$\ln(L_s^p/L_u^p)_{96}^{high}$	-0.735	1.359	-0.389	1.502
Foreign	0.017	0.130	0.081	0.273	$\ln(L_s^n/L_u^n)_{96}^{coll}$	-0.622	1.095	-0.930	1.173
R&D	0.057	0.231	0.178	0.384	$(L_s^p/(L_s^p+L_u^p))_{96}^{high}$	0.212	0.266	0.386	0.325
Training	0.308	0.462	0.589	0.493	$(L_s^p/(L_s^p+L_u^p))_{96}^{coll}$	0.008	0.039	0.026	0.079
$d_{u,96}^{p,high}$	0.017	0.128	0.057	0.233	$d_{u,96}^{n,coll}$	0.115	0.319	0.044	0.205
$d_{s,96}^{p,high}$	0.342	0.475	0.152	0.359	$d_{s,96}^{n,coll}$	0.607	0.489	0.323	0.469
No. Obs.	5706				4410				

	$D=0$		$D=1$			$D=0$		$D=1$	
Outcome Variable[(b)]	Mean	S.D.	Mean	S.D.	Outcome Variable	Mean	S.D.	Mean	S.D.
$\ln(L_s^p/L_u^p)_{06}$	-0.553	1.657	0.490	1.676	$(L_s^p/(L_s^p+L_u^p))_{06}$	0.340	0.333	0.559	0.337
$\ln(L_s^p/L_u^p)_{06}$	-1.202	1.202	-0.853	1.261	$(L_s^p/(L_s^p+L_u^p))_{06}$	0.166	0.253	0.278	0.266
$\ln(L_s/L_u)_{06}^{high}$	-0.577	1.683	0.645	1.722	$(L_s/(L_s+L_u))_{06}^{high}$	0.399	0.315	0.604	0.312
$\ln(L_s/L_u)_{06}^{coll}$	-3.050	1.090	-2.665	1.166	$(L_s/(L_s+L_u))_{06}^{coll}$	0.037	0.066	0.081	0.096
$\ln(L^n/L^p)_{06}$	-1.791	1.082	-1.639	1.093	$(L^n/(L^n+L^p))_{06}$	0.184	0.156	0.208	0.156

Notes: (a) The sample statistics for the explanatory variables that are used to estimate the decisions to import in Table G.7. (b) The sample statistics for the outcome variables that are used to estimate the skill demand equation (11). The superscript "*high*" and "*coll*" denote variables that are measured using highschool or college as the skill threshold, respectively.

gate skilled workers across occupations where $\ln(L_s/L_u)_{06} \equiv \ln(L_s^n + L_s^p/L_u^n + L_u^p)_{06}$ and $(L_s/(L_s+L_u))_{06} \equiv ((L_s^p + L_s^n)/(L_s^p + L_u^p + L_s^n + L_u^n))_{06}$. We keep the definition of skill, a highschool diploma or college degree, consistent across occupations in these measures and present both results in all of our regressions. Finally, our last outcome variable considers the log ratio of non-production workers to production workers, $\ln(L^n/L^p))_{06} \equiv \ln((L_s^n + L_u^n)/(L_s^p + L_u^p))_{06}$, or the fraction of non-production workers, $(L^n/(L^n+L^p))_{06} \equiv ((L_u^n + L_s^n)/(L_s^p + L_u^p + L_s^n + L_u^n))_{06}$, which are often used as measures of skill intensity in the existing literature.

The set of explanatory variables, X, includes the lagged value of the outcome variable in 1996, denoted by using the subscript "96" in place of "06," 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 $j = p, n$, and the relative wage ratios in 1996, denoted by $\ln(W_s/W_u)_{96}$.[12] In addition, X contains the plant's current export status, our estimate of Hicks-neutral

[12]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 $L_u^p = 0$.

productivity φ, the plant's capital stock, the local skilled-unskilled wage ratio,[13] a large set of dummy variables to capture differences across foreign ownership, R&D expenditures, worker training expenditures, industries and provinces. Using 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 (2015) 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.

3.4 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. Our primary instrument set includes location-specific transport costs and industry-specific measures of the fraction of imports shipped by air. We also consider industry-specific measures of imported input weight, changes in product-specific input and output tariffs, and tariff-based measures of export market access to check our benchmark results or control for the potential endogeneity of plant export behavior. We discuss the construction of each instrument in turn.

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 fraction of imports shipped by air, we rely on research that suggests that differences in trade responses across industries can arise from differences in the nature of delivery (e.g. air vs. water) or heaviness of the output. We extend this literature by combining measures the fraction of imports shipped by air (or of the weight of imports to Indonesia), industry-by-industry, with an Indonesian import input-output table to

[13]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 in the wage ratio reflect differences in demographics, experience, etc across regions.

construct an industry-level measure of the share of imports shipped by air.[14] The intuition for the transport mode instrument (air vs. water) comes directly from Hummels and Schaur (2013) which argues that exporters pay a premium to ship goods by air for faster delivery. Similarly, as Coşar and Demir (2015) recognize, heavier imports will be more costly to ship.

For each industry j, the variables $airshare_j$ and $weight_j$ measure the fraction of Indonesian imports shipped by air and the weight of Indonesian imports,

$$airshare_j = \frac{air\ value_j}{air\ value_j + ocean\ value_j}, \quad \text{and,} \quad weight_j = \ln\left(\frac{ocean\ weight_j}{ocean\ value_j}\right),$$

where $air\ value_j$ denotes the value of air shipments to Indonesia in 2006 and $ocean\ value_j$ ($ocean\ weight_j$) denotes the value (weight) of shipments to Indonesia by ocean in the same year.[15] We then combine this information with an import input-output table which provides us with the share of imports purchased from each industry in Indonesia.[16] Letting $share_{ij}$ represent industry i's import expenditure share on from industry j, our measures of import air share and import weight in industry i are constructed as

$$\text{Import airshare}_i = \sum_j share_{ij} \times airshare_j, \quad \text{Import weight}_i = \sum_j share_{ij} \times weight_j,$$

where $\sum_j\ share_{ij} = 1\ \forall\ i$ by construction. Not surprisingly, these two instruments are highly correlated. Because of this we largely focus on the variable capturing the fraction of imports shipped by air since the import weight variable adds little statistically significant variation to our first stage regressions.

For the fourth and fifth 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) and use the change in output and input tariff rates between 1996 and 2001 as our instrument. The sixth instrument is a tariff-based measure of market access for Indonesian exporters in destination markets. For each industry and year, we calculate the average tariff faced by firms in export markets where export shares are used as weights. We then

[14]The import input-output table is produced by BPS Indonesia.

[15]Specifically, we compute these measures for shipments to Indonesia from the US and Europe. We then take a simple average across both import sources. We thank Kerem Coşar who provided us with his Stata do files that compute variables $weight_j$ and $airshare_j$ from EU and US trade data sets.

[16]BPS Indonesia produces detailed input-output tables measuring of total purchases (all sources) at the industry-level or total domestic purchases. We construct measures import flows and import shares by subtracting the information in the domestic input-output table from the comparable information in the total input-output table. All input-output data is measured in 1995.

compute the change in export market access for each Indonesian industry. Full details of the construction of all instruments can be found in Appendix A.

Naturally, 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 address the potential concern for endogenous location choice, we focus on the 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. Likewise, we use the 1996 industry affiliation when assigning the import airshare to each plant. In this fashion, we guard against bias that would arise from plants which strategically switch to new industries in response to changes in the trade environment.[17]

4 Results

4.1 Benchmark IV Findings

Table 5 presents the results from estimating equation (5) by OLS and IV for production and non-production workers separately. Consistent with the model presented in Section 2, columns (1), (2), (5) and (6) use the log of the ratio of skilled production to unskilled production workers as its dependent variable. Unfortunately, because numerous plants have not hired even one skilled worker, using the log skill ratio leads to a non-trivial loss of plants. To address this potential source of bias, we repeat our exercise using the fraction of skilled workers in the plant's workforce as the dependent variable in columns (3), (4), (7) and (8). In all cases we restrict attention to the set of plant's which were not importing in 1996 so to isolate the impact of importing on plants who made their location decisions and determined their main product before they began using imported materials.

Columns (1)-(4) present results for production workers where a skilled production worker is defined as one who has successfully completed highschool. The OLS point estimate in column (1) suggests that importing significantly increases the relative demand for skilled workers within the production occupation by 48 log basis points. Similarly, column (3) indicates that importing increases the skilled fraction of the plant's workforce

[17]When using import weight or the tariff instruments we also match plants according to their 1996 industry affiliation.

by 5.5 percentage points. While these effects seem widely different at first blush, they are roughly consistent with each other since the fraction of skilled employees hired by initial non-importers prior to importing is typically quite small.

Columns (2) and (4), which instrument import status using both the distance to a major Indonesian port and fraction of imports shipped by air, suggest substantially larger effects. In fact, our findings suggest that importing increases the relative demand for skilled production workers by 371 log basis points and similarly increases the skilled fraction of the plant's labor force by 99 percentage points. Given the large magnitude of these estimates, it would be natural for the reader to be concerned that our point estimates suffer from the presence of weak instruments. However, as documented in Table G.7 of the Appendix, the first stage results suggest that our instruments are sufficiently strong (individually and jointly) to confidently estimate the causal impact of importing on the demand for skill. Furthermore, the p-values of Hansen's J test support the validity of the overidentification restrictions, providing some evidence that instruments are uncorrelated with the error term.

In a "standard" setting where we assume that there is no heterogeneity in β across plants in equation (5), 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, finding a large IV estimate is less puzzling because the IV estimator identifies the local average treatment effect in the sense that it only captures the impact of importing on plants that change their import status in response to variation in the instrumental variable. 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. One possible explanation is that starting to import is very costly: when the start-up cost of importing is large, only those plants which receive sufficiently large benefits from changing their import status (represented by high values of β) will choose to start importing. Moreover, it is important to recall the context of this estimate. In our sample, as reported in Table 4, the ratio of skilled to unskilled workers among importers is nearly double that of the average non-importer.

Columns (5)-(8) consider the same experiment for non-production workers. We again find that the IV estimates indicate that importing consistently has a large, positive and statistically significant impact on the demand skilled workers. It important to recognize that our definition of 'skill' has changed in this experiment; we now define a skilled worker as one with a college degree. Our findings suggest an important change in the organization

Table 5: Skill Demand Equation Across Occupations

Occupation	Production				Non-Production			
Threshold	Highschool				College			
Dependent Variable	$\ln(L_s^p/L_u^p)$		$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$		$\ln(L_s^n/L_u^n)$		$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Status	0.479***	3.705***	0.055***	0.990***	0.249***	3.643***	0.023	0.698***
	[0.108]	[1.320]	[0.017]	[0.280]	[0.094]	[1.130]	[0.015]	[0.238]
Export Status	-0.043	-0.263**	0.018	-0.053*	-0.174**	-0.486***	0.018	-0.034
	[0.074]	[0.127]	[0.013]	[0.028]	[0.076]	[0.143]	[0.012]	[0.023]
Wage_{06}^j	-0.101	-0.161	-0.010	-0.015	-0.064	-0.195	-0.030*	-0.026
	[0.164]	[0.191]	[0.023]	[0.029]	[0.120]	[0.148]	[0.016]	[0.019]
Capital	0.124***	0.072**	0.024***	0.012**	-0.015	-0.080**	0.014***	0.004
	[0.018]	[0.029]	[0.003]	[0.005]	[0.017]	[0.031]	[0.003]	[0.005]
Hicks-neutral, φ	-0.259***	-0.316***	-0.007	-0.021*	0.020	-0.054	0.030***	0.020*
	[0.049]	[0.061]	[0.008]	[0.011]	[0.049]	[0.061]	[0.008]	[0.010]
Foreign-Owned	0.068	-0.243	0.007	-0.105*	0.124	-0.312	0.015	-0.067
	[0.150]	[0.250]	[0.030]	[0.057]	[0.146]	[0.264]	[0.028]	[0.048]
R&D	0.025	-0.169	0.029*	-0.014	0.072	-0.148	0.024	-0.010
	[0.102]	[0.151]	[0.017]	[0.030]	[0.094]	[0.151]	[0.016]	[0.025]
Training	0.212***	0.124	0.048***	0.026*	0.020	-0.086	0.045***	0.025*
	[0.061]	[0.079]	[0.010]	[0.015]	[0.058]	[0.081]	[0.009]	[0.013]
Wage_{96}^j	-0.543***	-0.657***	-0.114***	-0.137***	0.331**	0.165	0.030*	0.013
	[0.190]	[0.226]	[0.030]	[0.040]	[0.133]	[0.181]	[0.018]	[0.023]
$\ln(L_s^j/L_u^j)_{96}$	0.362***	0.335***			0.279***	0.216***		
	[0.023]	[0.029]			[0.031]	[0.043]		
d_u^j	0.282	0.033			-0.025	-0.036		
	[0.201]	[0.264]			[0.124]	[0.149]		
d_s^j	-0.993***	-0.952***			-0.444***	-0.315***		
	[0.074]	[0.085]			[0.076]	[0.100]		
$\left(\frac{L_s^j}{L_s^j+L_u^j}\right)_{96}$			0.439***	0.383***			0.191***	0.163***
			[0.020]	[0.031]			[0.026]	[0.031]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.343	—	0.395	—	0.169	—	0.143	—
Hansen J p-value	—	0.153	—	0.141	—	0.336	—	0.185
No. Obs	3,139	3,111	4,445	4,410	2,108	2,089	4,021	3,988

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. The education threshold used to determine a skilled production worker is a highschool diploma, while the threshold used for a skilled non-production worker is a college degree. Import status is treated as an endogenous variable in columns (2), (4), (6) and (8). It is instrumented with both the distance to port and the share of imports shipped by air.

of non-production activities, although non-production workers represent a relatively small fraction of the workforce as documented is Section 3.[18] In fact, the IV estimates imply a 364 log basis point increase in demand skilled non-production workers and a 70 percentage point increase in the fraction of skilled non-production workers.

The control variables in Table 5 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 coefficient on relative wages in 2006 is negative, as expected, but insignificant.[19] The estimated coefficient on the lagged value of the outcome variable is positive, statistically significant, and consistently estimated to lie between 0 and 1. This may reflect either the persistence of unobserved characteristics that affect the plant's demand for skilled labor or the presence of adjustment costs associated with changing the plant's skill ratio.

Table 6 considers the plant-level demand for skill across all workers in a plant. Specifically, columns (1)-(4) consider the impact of importing on the relative demand for workers with at least a highschool diploma and columns (5)-(8) similarly examine the impact of importing on the relative demand for workers with a college degree. We also consider specifications where we use the log ratio of non-production to production workers or the fraction of the workforce engaged in non-production activities as a dependent variable in columns (9)-(12). These last exercises allow us to compare whether existing, common measures of skill-intensity, namely the fraction non-production workers in a plant, provide meaningfully different results from education-based measures of skill.[20]

[18]Our findings are strongest using the skill thresholds documented in Table 5. However, we continue to find marginally significant effects if we use alternative skill thresholds in each case. See the Appendix for details.

[19]In each case, the relative wage variable, the lagged dependent variable, and the lagged indicator variables are defined consistently with the skill threshold used in each regression. For instance, in columns (1)-(4) it is the relative differences between workers with a highschool degree and those without, while in columns (5)-(8) it measures the wage differences will college educated workers and those without a college degree. Details on the construction of these variables can be found in the Appendix.

[20]See Bernard and Jensen (1997), Harrison and Hanson (1999), Pavcnik (2003), and Biscourp and

The first two exercises in Table 6 present results which are similar to those in Table 5. In particular, the results from the regressions using highschool as the skill threshold closely resemble the results for production workers, while the results from the regressions which define college as the skill threshold are similar to our results which examine non-production workers alone. As above, in all cases we find that importing has a large, positive and highly significant impact on the demand for skilled labor. In comparison, the estimated coefficients on non-production intensity are positive in columns (9)-(12) but only marginally significant in one of four columns. The results are broadly consistent with our decomposition analysis and suggest that importing is mainly inducing skill-upgrading *within* each occupation group while the skill upgrading through reallocation from production workers to non-production workers plays, at best, the secondary role.

On the surface, our results might appear inconsistent with the result from Amiti and Cameron (2012, pages 285-286) which "shows that relative education intensity of production workers relative to nonproduction workers actually declined between 1996 and 2006 in importing and exporting firms relative to domestically-oriented firms." However, it is important to distinguish key differences across these empirical exercises. Specifically, Amiti and Cameron study the correlation of *current* import status with the relative growth of education-intensity across occupations, we focus on impact of *starting to import* on within-plant or within-plant-and-occupation skill upgrading.[21]

Tables 7 and 8 report a number of robustness checks for our benchmark results. We first estimate our specification in first differences by the IV regression. The differenced specification inherently controls for any time-invariant unobserved heterogeneity in equation (5) at the plant-level. Moreover, including both industry and region dummies allows us to condition our results on any differential trends across regions or industry. Last, in columns (2), (4), (6), (8) and (10), we drop changes in city-level relative wages as a control variable and instead directly control for the change in relative supply of skilled to unskilled labor in each location.[22]

Kramarz (2007) for examples of papers which use the ratio of non-production to production workers as a measure of skill.

[21] Table F.4 in the Appendix replicates Column 2 of Table 8 in Amiti and Cameron (2012) to the best of our ability and, furthermore, shows that using the change in import status between 1996 and 2006 in place of the 2006 import status in their specification leads to a result where the change in the relative education intensity is *positively* correlated with the change in import status between 1996 and 2006. Given our empirical findings, one possible interpretation of this positive correlation is that starting to import induces more education-upgrading within production workers than within non-production workers.

[22] Across all columns we focus on the skilled fraction of the plant's workforce because there are many plants that did not hire any skilled workers in 1996, which forces us to drop more plants from our sample in the log specification.

Table 6: Skill Demand Equation for All Workers in Levels

Threshold	Highschool				College				Occupation			
Dependent Variable	$\ln(L_s/L_u)$		$\left(\frac{L_s}{L_s+L_u}\right)$		$\ln(L_s/L_u)$		$\left(\frac{L_s}{L_s+L_u}\right)$		$\ln(L^n/L^p)$		$\left(\frac{L^n}{L^n+L^p}\right)$	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Import Status	0.409***	4.503***	0.042***	0.930***	0.162*	3.313***	0.016***	0.278***	0.020	1.411*	0.007	0.101
	[0.099]	[1.585]	[0.015]	[0.258]	[0.085]	[1.093]	[0.005]	[0.073]	[0.060]	[0.755]	[0.009]	[0.107]
Export Status	0.020	-0.293*	0.016	-0.052**	-0.230***	-0.543***	-0.009***	-0.030***	-0.099**	-0.222***	-0.015**	-0.023**
	[0.067]	[0.153]	[0.012]	[0.026]	[0.065]	[0.139]	[0.003]	[0.007]	[0.049]	[0.083]	[0.007]	[0.011]
Wage^j_{06}	-0.094	-0.157	0.008	0.004	-0.072	-0.177	-0.007*	-0.008	0.031	0.048	-0.002	-0.001
	[0.139]	[0.171]	[0.021]	[0.027]	[0.110]	[0.144]	[0.003]	[0.005]	[0.102]	[0.105]	[0.015]	[0.014]
Capital	0.116***	0.050	0.021***	0.010**	0.028*	-0.042	0.005***	0.002	0.027***	0.004	0.005***	0.003
	[0.016]	[0.033]	[0.003]	[0.005]	[0.016]	[0.033]	[0.001]	[0.001]	[0.010]	[0.016]	[0.001]	[0.002]
Hicks-neutral, φ	-0.188***	-0.259***	-0.010	-0.024**	0.015	-0.051	0.004*	0.000	-0.118***	-0.129***	-0.007	-0.007
	[0.047]	[0.062]	[0.007]	[0.010]	[0.044]	[0.058]	[0.002]	[0.003]	[0.031]	[0.035]	[0.005]	[0.005]
Foreign-Owned	0.013	-0.314	0.017	-0.091*	0.144	-0.415	0.005	-0.027*	-0.051	-0.249*	-0.011	-0.024
	[0.152]	[0.269]	[0.027]	[0.054]	[0.130]	[0.278]	[0.009]	[0.016]	[0.099]	[0.147]	[0.014]	[0.020]
R&D	0.192**	-0.039	0.030*	-0.012	0.163**	0.021	0.022***	0.010	0.168**	0.105	0.025**	0.022*
	[0.092]	[0.163]	[0.016]	[0.028]	[0.077]	[0.123]	[0.006]	[0.009]	[0.075]	[0.090]	[0.012]	[0.013]
Training	0.278***	0.203***	0.044***	0.023	0.114**	-0.004	0.017***	0.009**	0.061	0.021	0.012**	0.009
	[0.055]	[0.075]	[0.009]	[0.014]	[0.053]	[0.085]	[0.002]	[0.004]	[0.037]	[0.047]	[0.005]	[0.006]
Wage^j_{96}	-0.619***	-0.769***	-0.114***	-0.134***	0.427***	0.219	0.017***	0.011*	0.109	0.034	0.034**	0.026
	[0.172]	[0.217]	[0.027]	[0.038]	[0.119]	[0.177]	[0.004]	[0.006]	[0.119]	[0.125]	[0.016]	[0.016]
$\ln(L_s/L_u)_{96}$	0.449***	0.409***			0.384***	0.311***						
	[0.023]	[0.033]			[0.026]	[0.044]						
d_u	-0.074	-0.063			-0.313**	-0.231						
	[0.047]	[0.060]			[0.136]	[0.187]						
d_s	0.058	0.022			0.139**	0.104						
	[0.061]	[0.075]			[0.058]	[0.081]						
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$			0.484***	0.436***			0.282***	0.225***				
			[0.018]	[0.029]			[0.038]	[0.050]				
$\ln(L^n/L^p)_{96}$									0.392***	0.397***		
									[0.019]	[0.020]		
d^p									-0.119***	-0.131***		
									[0.035]	[0.037]		
d^n									0.094***	0.082**		
									[0.032]	[0.035]		
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$									-0.119***	-0.131***		
									[0.035]	[0.037]		
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.395	—	0.440	—	0.340	—	0.247	—	0.251	—	0.237	—
Hansen J p-value	—	0.234	—	0.202	—	0.782	—	0.284	—	0.360	—	0.874
No. Obs	3,434	3,405	4,445	4,410	1,657	1,641	4,445	4,410	4,021	3,988	4,445	4,410

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in columns (2), (4), (6), (8), (10) and (12). It is instrumented with both the distance to port and the share of imports shipped by air.

Table 7: Robustness Checks: The Skill Demand Equation in Differences

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dep. Var.	$\Delta\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$		$\Delta\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$		$\Delta\left(\frac{L_s}{L_s+L_u}\right)$		$\Delta\left(\frac{L_s}{L_s+L_u}\right)$		$\Delta\left(\frac{L^n}{L^n+L^p}\right)$	
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Import Status	0.779**	0.801**	0.255	0.251	0.540**	0.541**	0.175**	0.178**	0.259*	0.261*
	[0.318]	[0.325]	[0.217]	[0.219]	[0.250]	[0.252]	[0.070]	[0.071]	[0.157]	[0.158]
Δ Export Status	-0.010	-0.010	0.002	0.001	0.003	0.005	-0.007	-0.007	-0.015	-0.015
	[0.022]	[0.022]	[0.017]	[0.017]	[0.018]	[0.018]	[0.005]	[0.005]	[0.011]	[0.011]
Δ Wage	0.046		-0.012		0.056**		-0.007*		-0.008	
	[0.028]		[0.016]		[0.023]		[0.004]		[0.015]	
Δ Skill Supply		0.034**		-0.007		0.039***		-0.002		0.001
		[0.016]		[0.008]		[0.013]		[0.002]		[0.008]
Δ Capital	-0.005	-0.005	0.007**	0.007**	-0.005	-0.004	0.001	0.001	0.000	0.000
	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.001]	[0.001]	[0.002]	[0.002]
Δ Hicks-neutral, φ	-0.043***	-0.045***	0.024**	0.024***	-0.040***	-0.041***	0.001	0.001	-0.013**	-0.013**
	[0.011]	[0.011]	[0.009]	[0.009]	[0.010]	[0.009]	[0.003]	[0.003]	[0.006]	[0.006]
Δ Foreign-Owned	-0.002	-0.003	-0.022	-0.021	0.006	0.003	-0.006	-0.006	0.014	0.014
	[0.038]	[0.038]	[0.031]	[0.031]	[0.030]	[0.030]	[0.012]	[0.012]	[0.017]	[0.017]
Δ R&D	-0.010	-0.009	-0.020	-0.021	-0.012	-0.011	-0.005	-0.005	-0.011	-0.012
	[0.027]	[0.027]	[0.019]	[0.019]	[0.021]	[0.021]	[0.007]	[0.007]	[0.014]	[0.014]
Δ Training	-0.011	-0.011	0.012	0.012	-0.003	-0.003	0.002	0.002	0.001	0.001
	[0.014]	[0.014]	[0.011]	[0.011]	[0.011]	[0.012]	[0.003]	[0.003]	[0.007]	[0.007]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.334	0.311	0.369	0.392	0.214	0.253	0.159	0.142	0.137	0.118
No. Obs	3,366	3,361	3,366	3,345	3,366	3,361	3,366	3,345	3,366	3,361

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. The education threshold used to determine a skilled production worker is a highschool diploma, while the threshold used for a skilled non-production worker is a college degree. Import status is treated as an endogenous variable in all regressions. It is instrumented with both the distance to port and the share of imports shipped by air.

Table 7 reports point estimates that are consistently large and positive regardless of whether we control for changes in relative wages or the relative supply of skilled labor. Within occupations, we continue to find that importing has a highly significant impact on the relative demand for skill among production workers, but less so among non-production workers. Examining all workers together, we again find strongly significant results when we use either skill threshold and marginally significant point estimates when we consider the fraction of non-production workers. Across all cases, we recover substantially smaller point estimates in the first differenced specification relative to the benchmark results.[23]

Table 8 presents a series of further robustness checks. Although we only report key coefficients in Table 8, a full set of controls are included in each regression. The top panel (regressions (1)-(10)) reconsiders our benchmark framework but uses our alternative measure of the relative supply of skilled labor in each location in place of the skill premium. Importing continues to have a large, positive impact on the demand for skill, while the coefficients on the relative supply of skilled labor are positive.

The second panel (regressions (11)-(20)) includes our additional instruments for the decision to import; specifically, we augment our benchmark instrument set with the weight of imported goods and the tariffs faced by importers on intermediate inputs. In each case we observe a coefficient which is similar is size and magnitude to our benchmark IV findings in Tables 5 and 6.

The third panel (regressions (21)-(30)) includes both a measure of the plant-level intensity of importing, the fraction of total intermediates imported from abroad, along with the import status dummy variable. By including both import status and import intensity we investigate the degree to which the impact of importing on plant-level skill composition is manifested through changes in the intensive or extensive import margins. The import status coefficient is always positive and nearly always statistically significant. In contrast, import intensity is consistently estimated to negative and is never significant. As such, we conclude the plant-level changes in skill demand largely occur through the extensive margin of importing.[24]

In the fourth panel (regressions (31)-(40)) we replace our measure of Hicks-neutral productivity with a conventional measure of TFP. Specifically, we replace Hicks-neutral TFP with an estimate of the Solow residual from a Cobb-Douglas production function

[23]The first differenced specification could bias the point estimates downwards if the specification with lagged dependent variable is the correct specification. The Appendix D provides a detailed argument that extends the argument of Angrist and Pischke (2008, pp. 184-185) in the context of the IV regression.

[24]If we exclude import status, the import intensity is always positive and statistically significant.

which uses capital, materials, production workers and non-production workers as inputs. Again, we recover very similar point estimates relative to our benchmark results.[25]

The fifth panel addresses the concern that exporting is likely to be an endogenous decision in this context. For instance, given the evidence that importing and exporting are closely related activities (see Kasahara and Lapham, 2013), ignoring the endogeneity of the plant's export decision may lead to bias in the estimated coefficient on import status. Regressions (41)-(50) estimate the skill equation while instrumenting both import and export status with transport costs, air share, and the changes output tariffs and market access tariffs as defined in Section 3.[26] We continue to find that importing has a large, positive impact of the demand for skilled workers. In contrast, the impact of exporting on the demand for skill is estimated to be insignificantly different from zero in all but one column.

Feenstra and Hanson (1996, 1997) present a model with a continuum of goods where the most skill-intensive goods in developing countries correspond to the least skill-intensive goods in developed countries. 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. The Feenstra and Hansen hypothesis does not appear to hold in our data since none of the estimated coefficients on exporting are significantly positive in regression (41)-(50).

[25]Hicks-neutral productivity is estimated to take a negative coefficient in Tables 5-6, while our naively estimated TFP takes the opposite sign in the fourth robustness check of Table 8, even if it is always insignificant in this latter case. While these results may seem contradictory, they are 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.

[26]First stage results for the decision to export can be found in the Appendix.

Table 8: Robustness Checks

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dep. Var.	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	Skill Supply Controls									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	2.448*	0.778***	3.783***	0.513**	3.388**	0.660***	3.041**	0.226***	0.786	0.024
	[1.364]	[0.274]	[1.344]	[0.231]	[1.684]	[0.238]	[1.268]	[0.070]	[0.812]	[0.120]
Skill Supply$_{06}$	0.244***	0.050***	0.131**	0.017**	0.185***	0.053***	0.029	0.004*	0.035	0.003
	[0.070]	[0.012]	[0.061]	[0.008]	[0.065]	[0.011]	[0.059]	[0.002]	[0.039]	[0.006]
Skill Supply$_{96}$	-0.006	-0.008	-0.075	0.009	0.019	-0.006	0.038	0.003	0.052	0.006
	[0.083]	[0.015]	[0.073]	[0.008]	[0.080]	[0.013]	[0.068]	[0.002]	[0.045]	[0.006]
	Large IV set									
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Import Status	3.240***	0.864***	3.498***	0.672***	4.105***	0.818***	3.191***	0.267***	1.557**	0.116
	[1.247]	[0.254]	[1.049]	[0.230]	[1.496]	[0.235]	[1.072]	[0.069]	[0.746]	[0.108]
	Import Intensity									
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Import Status	7.309*	1.640**	5.498	1.420**	8.128*	1.458**	3.825	0.445**	2.945	0.148
	[3.974]	[0.658]	[3.640]	[0.675]	[4.632]	[0.600]	[2.554]	[0.179]	[1.936]	[0.238]
Import Share	-8.143	-1.479	-2.563	-1.445	-7.487	-1.200	-0.715	-0.354	-3.417	-0.116
	[8.230]	[1.365]	[6.897]	[1.323]	[8.824]	[1.233]	[3.979]	[0.375]	[3.768]	[0.475]
	TFP Measurement									
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
Import Status	3.151***	0.947***	3.885***	0.724***	3.968***	0.885***	3.264***	0.275***	1.226*	0.089
	[1.211]	[0.270]	[1.133]	[0.238]	[1.451]	[0.248]	[1.072]	[0.071]	[0.729]	[0.105]
Solow Residual	0.001	0.011	0.023	0.014	0.022	0.008	0.031	0.003	-0.032	-0.000
	[0.044]	[0.009]	[0.050]	[0.008]	[0.046]	[0.008]	[0.048]	[0.002]	[0.027]	[0.004]
	Instrumenting Export Status									
	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)	(49)	(50)
Import Status	2.977**	0.909***	4.240**	0.888***	4.446**	0.947***	0.933	0.191**	0.739	0.014
	[1.289]	[0.305]	[1.701]	[0.330]	[1.840]	[0.300]	[0.893]	[0.075]	[0.825]	[0.121]
Export Status	-0.551	0.073	0.232	0.136	0.142	0.088	-1.419***	-0.019	-0.719	-0.093
	[0.558]	[0.124]	[0.859]	[0.116]	[0.620]	[0.120]	[0.492]	[0.029]	[0.470]	[0.070]
	Standards									
	(51)	(52)	(53)	(54)	(55)	(56)	(57)	(58)	(59)	(60)
Standards	5.354*	1.365**	1.931*	0.828**	5.976*	1.220**	0.502	0.222**	1.053	-0.078
	[3.000]	[0.618]	[1.148]	[0.393]	[3.083]	[0.559]	[0.816]	[0.093]	[1.230]	[0.178]
	Capital-Skill Complementarity									
	(61)	(62)	(63)	(64)	(65)	(66)	(67)	(68)	(69)	(70)
Import Status	5.716***	1.476***	3.639*	0.525	7.500***	1.460***	3.113**	0.273**	2.609**	0.184
	[2.130]	[0.464]	[2.060]	[0.378]	[2.901]	[0.465]	[1.521]	[0.137]	[1.159]	[0.126]
Capital-Skill Comp.	0.388	0.081	-0.021	-0.017	0.513	0.114	-0.143	0.002	0.246	0.004
	[0.511]	[0.090]	[0.567]	[0.093]	[0.862]	[0.108]	[0.423]	[0.031]	[0.189]	[0.016]

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. Industry and region fixed effects are included in all regressions. Columns (51)-(60) focus on the sample of non-exporters since exporting and production standardization are highly correlated activities.

Although we document evidence that importing leads to an increase in the demand for skill, 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).[27] The use of standards may allow for improved coordination with foreign suppliers, facilitating the adoption of foreign skill-biased technology.

In the sixth panel, we estimate the effect of standards on the demand for skilled production workers using our benchmark specifications of Table 5 and 6 but replacing the import dummy with a dummy for standardized production, where we focus on the sample of non-exporters since standardization is closely associated with exporting activities.[28] Regressions (51)-(60) indicate that the adoption of standards significantly increases the demand for both skilled production and non-production workers.

To further explore the relationship between standardization and importing, we also consider a linear regression model of the decision to adopt standardized production. In particular, we regress our standardization dummy variable on import status and a full set of controls using the sample of non-exporting firms.[29] In all columns of Table 9 we find that the point estimate on importing is both large and positive. Moreover, in 8 out of 10 columns of Table 9 the estimate is reported to be at least marginally significant. Although these results are hardly overwhelming, they are consistent with the hypothesis that importing induces standardization and, thus, skill-biased technological change.

[27] 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.

[28] Transport costs are typically strong predictors of the use of standards.

[29] Explicitly instrumenting for endogenous export decisions returns very similar point estimates and statistical significance for the import status variable.

Table 9: Importing and Standardized Production

Dep. Var.	Standards									
Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	1.491*	1.425*	1.819*	1.622*	2.268	1.395*	1.113	1.851*	1.467*	1.517*
	[0.877]	[0.851]	[1.002]	[0.966]	[2.112]	[0.843]	[1.282]	[1.055]	[0.850]	[0.826]
Control Vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.460	0.428	0.399	0.379	0.647	0.421	0.202	0.411	0.472	0.426
No. Obs	3,329	3,329	3,329	2,958	2,720	3,329	1,194	3,329	2,958	3,329

Notes: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. The education threshold used to determine a skilled production worker is a highschool diploma, while the threshold used for a skilled non-production worker is a college degree. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air. All full set of control variables is included in each regression. Detailed results are reported in the Appendix.

Finally, we also consider whether importing leads to skill-upgrading through a capital-skill complementarity mechanism, rather than the framework posited in Section 2. We first extend our model to allow for potential capital-skill complementarity as presented in Appendix E. The firm's cost minimization problem will then imply that the relative demand for skilled labor can be written as:

$$\frac{L_s^j}{L_u^j} = \left(\beta \frac{W_u}{W_s}\right)^{\sigma_j} (A^j)^{\sigma_j - 1} \left(\frac{K}{(L_s^p + L_s^n)}\right)^{(\sigma_j - 1)(1-\beta)}. \tag{10}$$

It is clear that capital-skill complementarity implies adding one additional variable to our benchmark empirical specification, the log ratio of capital to total (production and non-production) skilled labor, $\ln\left(K/(L_s^p + L_s^n)\right)$. Unfortunately, including $\ln\left(K/(L_s^p + L_s^n)\right)$ on the right-hand side of equation (5) is likely to induce endogeneity bias since skilled labor determines both outcome and explanatory variables. As such, regressions (61)-(70) of Table 8 document IV estimates of the impact of importing on the demand skilled labor while also instrumenting the endogenous capital-skill control using lagged (i.e., 1996) values of $\ln\left(K/(L_s^j + L_s^j)\right)$ as an additional instrument. We find that the impact of importing on the demand for skilled production workers is nearly unaffected by controlling for capital-skill complementarity; the point estimates on the import status variable are of a similar magnitude and significance as the benchmark regressions in Tables 5 and 6.

5 Marginal Treatment Effects

5.1 Propensity Scores

We estimate the import probabilities for each plant using a logit specification where we include the interaction terms between instruments and the lagged value of the outcome variable in 1996 as well as dummy variables for plants that did not hire any skilled or unskilled workers in 1996. Transport costs, air shares, and weights are included as instruments. Table B.3 in the Appendix reports the estimate of the coefficient and marginal derivative for each variable with bootstrapped standard errors, where we find that transport costs and air shares are always a strong predictor of importing.

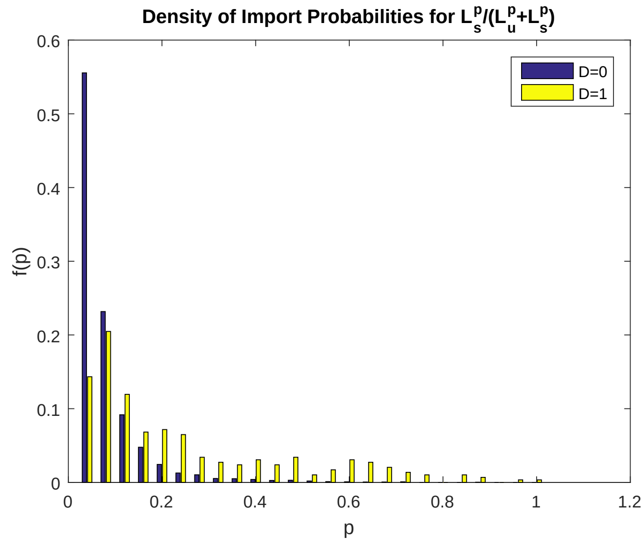
Figure 2 plots the distribution of estimated propensity scores for importing and non-importing plants. It is evident that the common support of the propensity scores across importing and non-importing plants does not span the full unit interval. For this reason, we restrict our computation of treatment 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 last row of Table 10; specifically, treatment effects are computed over the region where the minimum and maximum values are given by the 1^{st} percentile and the 99^{th} percentile values of the 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.

5.2 Treatment Effects

Figure 3 plots the estimated relationships between the MTE and U_D along with 90 percent (equal-tailed) bootstrap confidence bands across 5 different outcome variables using the share of skilled workers as the dependent variable.[30] As shown in Figure 3(a)-(d), the estimated MTE curve for production workers is well above zero for small values of U_D and is downward sloping for all of our four education-based skill measures. These findings provide evidence that plants self-selected into importing based on the plant-specific, unobserved component of the net benefit from importing—among plants that choose to

[30]The import decision model is estimated for each bootstrap sample so that the first stage estimation error is taken into account. Table B.1 in the Appendix reports the estimates of the skill demand equation using the sample of plants for which the estimated propensity scores are on the estimated common support. The results for using the log of the skill ratios as the outcome variables are reported in Figure B.5 and are similar to those in Figure 3.

Figure 2: Support of Estimated Propensity Scores



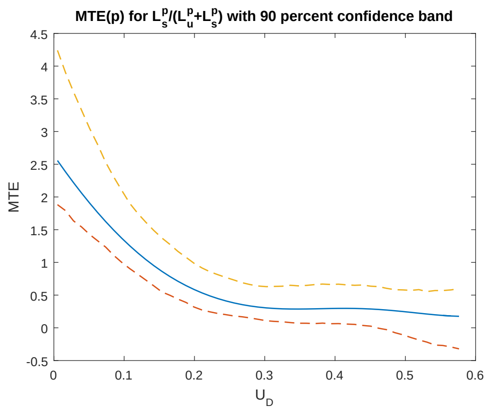
import when their propensity scores, estimated in terms of observables, are low, the unobserved ability to adopt the skilled biased technology must be high. On the other hand, in Figure 3(e), when we use the share of non-production workers as the outcome variable, the estimated MTE curve is not significantly different from zero across all values of U_D.

Figure 4 graphs the estimated weights for computing different treatment parameters when we use $L_s^p/(L_s^p + L_u^p)$ as the outcome variable. While the TT heavily overweights individual plants with low levels of U_D, the TUT overweights those with high levels of U_D. By construction, the ATE equally weights different values of U_D. If the MTE curve were flat, there would be no self-selection based on the unobservable gains, and the ATE would equal to the TT and the TUT. The fact that the estimated MTE curve is downward sloping suggests the presence of selection bias from the unobserved, heterogeneous return to importing and invalidates the use of a simpler propensity score matching methods for estimating the ATE in our context.

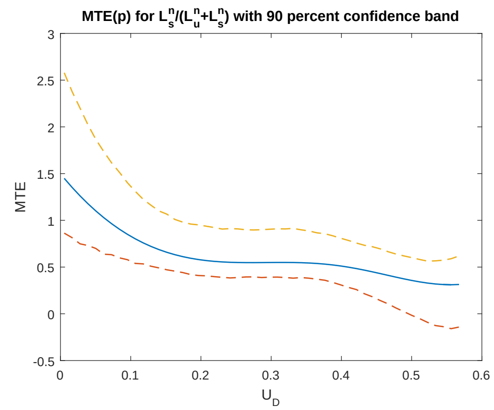
Table 10 reports the estimates of various summary measures of the impact of importing on skill demand: the ATE, the TT, the TUT, and policy relevant treatment effects (the MPRTEs and the PRTEs). These treatment effects are computed as the weighted averages of the MTE, where these weights integrate to one over the restricted support reported in the second to last row of Table 10. Bootstrap standard errors and the 90 percent equal-tailed bootstrap confidence interval are reported in square brackets and parentheses, respectively. Appendix B discusses the details of our estimation procedure.

The first two columns of Table 10 report the estimated treatment effects for production

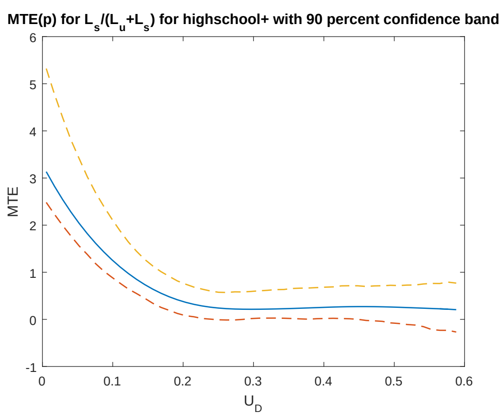
Figure 3: Estimated MTE



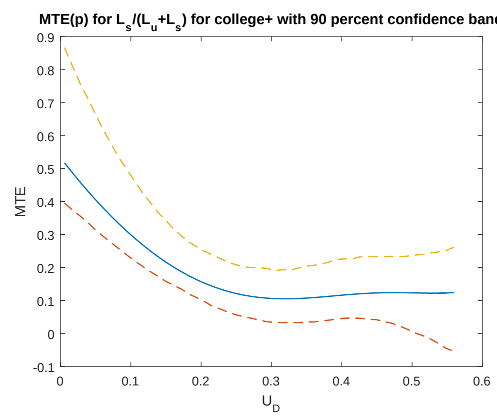
(a) Production, Highschool



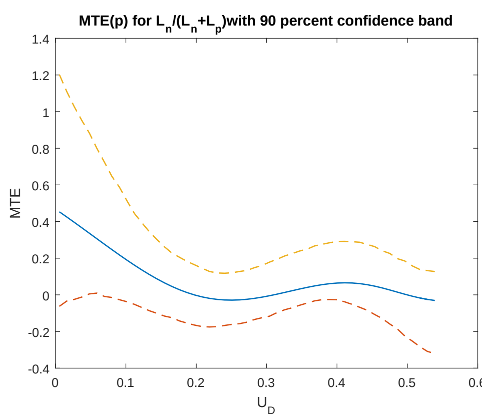
(b) Non-Production, College



(c) All, Highschool

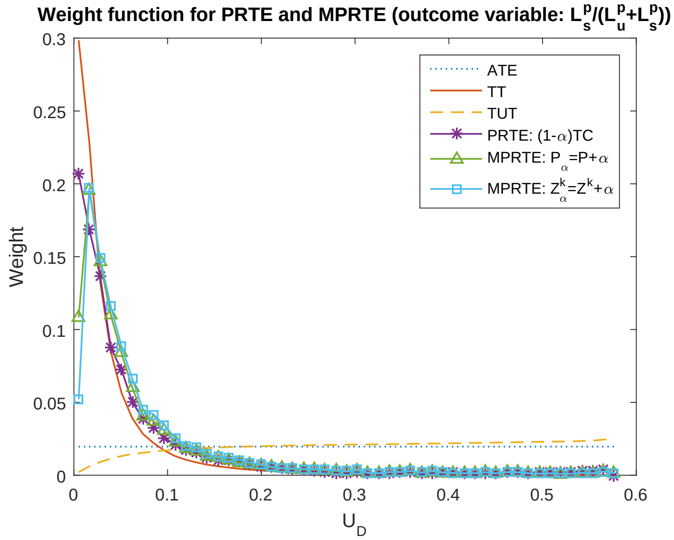


(d) All, College



(e) All, Occupation

Figure 4: Estimated Weights for ATE, TT, TUT, MPRTEs, and PRTE (Dependent variable: $L_s^p/(L_s^p + L_u^p)$)



workers. 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 production workers across different groups of plants. Furthermore, the TT is estimated to be substantially larger than the ATE which, in turn, is larger than the TUT. This is potentially indicative of substantial unobserved heterogeneity in the effect of importing on skill demand across plants and that plants with greater returns from importing self-select into importing. 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.

As Columns (3)-(8) of Table 10 show, we observe similar patterns for the ordering among the TT, the ATE, and the TUT across different education-based measures of skill demand. However, the skill measures based on the ratio of non-production to production workers reported in columns (9)-(10) indicate that the ATE, the TT, and the TUT are not significantly different from zero.

Table 10: Treatment Effects of Importing on Skill Demand

Occupation Threshold	Production Highschool		Non-Production College		All Highschool		All College		All Occupation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Var.	$\ln\left(\frac{L_s^p}{L_u^p}\right)_{06}$	$\left(\frac{L_s^p}{L_u^p+L_s^p}\right)_{06}$	$\ln\left(\frac{L_s^n}{L_u^n}\right)_{06}$	$\left(\frac{L_s^n}{L_u^n+L_s^n}\right)_{06}$	$\ln\left(\frac{L_s}{L_u}\right)_{06}$	$\left(\frac{L_s}{L_u+L_s}\right)_{06}$	$\ln\left(\frac{L_s}{L_u}\right)_{06}$	$\left(\frac{L_s}{L_u+L_s}\right)_{06}$	$\ln\left(\frac{L^p}{L^p}\right)_{06}$	$\left(\frac{L^p}{L^p+L^p}\right)_{06}$
ATE	1.897	0.690	3.231	0.623	2.390	0.651	2.099	0.188	0.496	0.084
	[0.926]	[0.175]	[0.883]	[0.146]	[0.734]	[0.199]	[0.751]	[0.046]	[0.608]	[0.102]
	(0.70,3.82)	(0.51,1.07)	(2.75,5.67)	(0.45,0.95)	(1.72,4.08)	(0.46,1.13)	(1.31,3.71)	(0.14,0.29)	(-0.34,1.69)	(-0.04,0.29)
TT	5.041	2.127	4.193	1.235	6.377	2.477	3.153	0.442	1.663	0.368
	[2.158]	[0.581]	[1.521]	[0.408]	[2.223]	[0.703]	[1.255]	[0.113]	[1.704]	[0.312]
	(2.66,9.61)	(1.59,3.46)	(3.11,7.95)	(0.74,2.14)	(4.62,12.04)	(1.96,4.18)	(1.91,6.09)	(0.34,0.73)	(-0.31,5.36)	(-0.01,0.98)
TUT	1.543	0.550	3.093	0.563	2.027	0.492	1.905	0.163	0.379	0.057
	[0.871]	[0.145]	[0.824]	[0.131]	[0.671]	[0.164]	[0.694]	[0.043]	[0.553]	[0.086]
	(0.46,3.30)	(0.39,0.85)	(2.67,5.38)	(0.39,0.85)	(1.35,3.52)	(0.32,0.88)	(1.10,3.35)	(0.11,0.25)	(-0.40,1.42)	(-0.06,0.23)
MPRTE	4.379	1.859	3.904	1.104	5.692	2.091	2.932	0.393	1.471	0.313
$(P_\alpha^* = P + \alpha)$	[1.867]	[0.494]	[1.356]	[0.351]	[1.911]	[0.588]	[1.135]	[0.098]	[1.455]	[0.267]
	(2.34,8.32)	(1.39,2.99)	(2.98,7.32)	(0.69,1.89)	(4.18,10.48)	(1.65,3.51)	(1.79,5.59)	(0.31,0.64)	(-0.19,4.58)	(-0.01,0.85)
MPRTE	4.241	1.793	3.834	1.078	5.500	2.000	2.896	0.384	1.425	0.301
$(Z_\alpha^{k*} = Z^k + \alpha)$	[1.783]	[0.477]	[1.319]	[0.340]	[1.800]	[0.568]	[1.114]	[0.095]	[1.372]	[0.257]
	(2.27,8.07)	(1.34,2.88)	(2.90,7.16)	(0.68,1.83)	(4.11,10.01)	(1.55,3.36)	(1.76,5.53)	(0.30,0.62)	(-0.13,4.37)	(-0.00,0.81)
PRTE	4.518	1.915	3.949	1.138	5.819	2.185	2.951	0.405	1.507	0.323
	[6.640]	[0.518]	[1.394]	[0.366]	[2.236]	[0.623]	[1.143]	[0.102]	[1.494]	[0.273]
	(2.43,8.73)	(1.43,3.10)	(2.99,7.40)	(0.70,1.95)	(4.30,10.74)	(1.72,3.68)	(1.81,5.64)	(0.31,0.66)	(-0.19,4.69)	(-0.00,0.87)
Support$^{(c)}$	[0.01,0.58]	[0.01,0.58]	[0.00,0.57]	[0.01,0.57]	[0.01,0.60]	[0.01,0.59]	[0.01,0.54]	[0.01,0.56]	[0.00,0.56]	[0.01,0.54]
No. of Obs.$^{(d)}$	2820	3997	1898	3992	3452	3985	2216	3967	3960	4000

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 examines the robustness of our results using different specifications and estimation methods, where we focus on the share of skilled workers within production workers or non-production workers as the outcome variable. Columns (1) and (5) report the estimates of treatment effects when we use conventional TFP in place of our estimated Hicks-neutral productivity. In columns (2) and (6), we estimate the partial linear model (11) where we use a sieve estimator based on the 4th order polynomials in $P(Z)$ instead of the local polynomial estimator. Columns (3) and (7) consider a specification of the skill demand equation without any interactions between the instruments and the lagged outcome variable, while columns (4) and (8) estimate treatment effects over the estimated common support instead of the subset of the common support defined by the 1^{st} percentile and the 99^{th} percentile of observations that are on the common support.[31] The estimates of the ATE, the TT, and the TUT in columns (1)-(8) of Table 11 are significantly positive and exhibit the patterns similar to those reported in columns (2) and (4) of Table 10.

5.3 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 much more skill-upgrading would be induced by *further* changes in policy related variables. 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) as 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 10 percent so that $P^*(Z)$ is set to the propensity score under the alternative transport cost of $TC^* = 0.9TC$. 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

[31] 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 B.3 except that, in columns (3) and (7), we exclude the interaction terms between the instruments and the 1996 value of the log of skill ratio from the set of explanatory variables.

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.[32] We also compute the marginal version of the 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 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)-(8) of the lower panel of Table 10, the estimates of the MPRTEs and the PRTE indicate that the subset of plants that would be induced to start importing by further policy change would substantially increase their demand for skilled workers when we use the education-based skill measures. These estimates are not sensitive to changes in specifications and estimation methods on the whole as shown in the lower panel of Table 11. In contrast, when we use the share of non-production workers as the outcome variable, the estimates of the MPRTEs and the PRTE are not significantly different from zero, providing no evidence that further importing would affect the demand for non-production workers relative to production workers.

[32] As discussed in Carneiro, Heckman, and Vytlacil (2010), the PRTE is not identifiable without strong support conditions. To compute the estimate of what the 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 are larger than the maximum value of the restricted support so that all of the propensity scores under the alternative policy lie on the restricted support.

Table 11: Robustness Check: Treatment Effects of Importing on Skill Demand for Production Workers

Occupation Threshold	Production Highschool				Non-Production College			
Dep. Var.	$\left(\frac{L_s^p}{L_u^p+L_s^p}\right)_{06}$				$\left(\frac{L_s^n}{L_u^n+L_s^n}\right)_{06}$			
	(1) Replace φ with TFP	(2) Use Sieve in place of Local Poly.	(3) No Interaction with Z	(4) Treatment Effects over Common Support	(5) Replace with TFP	(6) Use Sieve in place of Local Poly.	(7) No Interaction with Z	(8) Treatment Effects over Common Support
ATE	0.690	0.645	0.819	0.539	0.623	0.502	0.547	0.911
	[0.173]	[0.158]	[0.209]	[0.281]	[0.146]	[0.150]	[0.139]	[0.270]
	(0.51,1.07)	(0.48,1.00)	(0.60,1.27)	(0.18,1.04)	(0.45,0.95)	(0.28,0.77)	(0.39,0.86)	(0.82,1.74)
TT	2.127	2.168	2.370	2.140	1.235	0.970	1.573	1.242
	[0.583]	[0.560]	[0.731]	[0.592]	[0.406]	[0.473]	[0.454]	[0.415]
	(1.59,3.46)	(1.63,3.49)	(1.50,3.90)	(1.56,3.46)	(0.76,2.14)	(0.14,1.78)	(1.11,2.57)	(0.76,2.15)
TUT	0.550	0.509	0.671	0.435	0.563	0.460	0.447	0.910
	[0.143]	[0.135]	[0.169]	[0.298]	[0.131]	[0.139]	[0.118]	[0.292]
	(0.39,0.86)	(0.36,0.81)	(0.50,1.04)	(0.01,0.95)	(0.40,0.85)	(0.24,0.70)	(0.30,0.69)	(0.79,1.81)
MPRTE	1.859	1.855	2.055	1.861	1.104	0.877	1.343	1.108
	[0.496]	[0.466]	[0.607]	[0.500]	[0.350]	[0.389]	[0.383]	[0.355]
	(1.41,2.96)	(1.44,2.94)	(1.34,3.32)	(1.33,2.97)	(0.70,1.87)	(0.23,1.56)	(0.96,2.19)	(0.70,1.90)
MPRTE2	1.793	1.776	1.996	1.795	1.078	0.858	1.296	1.080
	[0.478]	[0.447]	[0.589]	[0.483]	[0.339]	[0.371]	[0.372]	[0.347]
	(1.37,2.86)	(1.37,2.81)	(1.30,3.21)	(1.29,2.85)	(0.68,1.82)	(0.25,1.52)	(0.92,2.11)	(0.68,1.84)
PRTE	1.915	1.928	2.140	1.966	1.138	0.902	1.403	1.162
	[0.519]	[0.492]	[0.644]	[1.291]	[0.364]	[0.413]	[0.402]	[0.425]
	(1.45,3.08)	(1.48,3.09)	(1.39,3.49)	(1.34,3.19)	(0.72,1.94)	(0.20,1.61)	(0.99,2.30)	(0.70,2.01)
Support$^{(c)}$	[0.01,0.58]	[0.01,0.58]	[0.01,0.56]	[0.00,0.87]	[0.01,0.57]	[0.01,0.57]	[0.01,0.55]	[0.00,0.87]
No. of Obs.$^{(d)}$	3997	3997	4006	3997	3992	3992	3993	3992

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.

6 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 adoption of skill-biased technology. In our model 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 for production workers and one with a college education for non-production workers, we find that importing greatly increases the demand for educated workers among Indonesian importers within each of occupation categories. We also document evidence that the effect of importing on the demand for educated workers is heterogeneous across plants. In particular, plants that 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 educated workers among new importers. Notably, however, when we repeat our experiments using a conventional measure of relative skill demand, defined as the ratio of non-production to production workers, we often find no significant impact of importing on the demand for skilled labor.

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(Not For Publication) Supplementary Appendix to "Does Importing Intermediates Increase the Demand for Skilled Workers? Plant-level Evidence from Indonesia"

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A Data Description

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.

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. We define production workers with more than high-school education or non-production workers with more than college education as skilled workers. Using this definition we count the number of skilled and unskilled workers for each occupation category and each plant.

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

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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).[1] 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 of buildings, machines, and vehicles in year t.

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 $K_{i,2006}^{impute} = 0.9\exp(X'_{i,2005}\hat{\alpha}) + Investment_{i,2005}$. 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 construct the imputed value of capital at the beginning of year 1996 using 1995 data in the same way.

Other Plant 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 Variables

The plants in our data locate across 33 provinces and 397 regions (kabupaten/kota) in Indonesia. This detailed location information allows us to take use of the variations in the local wages and the transportation cost.

Wage

We use the household survey data (SAKERNAS—Indonesian Labour Force Survey) to estimate the skill premium in each region after controlling for other personal characteristics of workers that may affect their

[1] 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 deflators of construction goods, machines and vehicles are used to extend the original price index to 2007.

wages. Specifically, using the sample of employed workers in the household survey for 1996 and 2006, we estimate the following Mincer regression:

$$\log(Wage_{ir}) = \beta_g Gender_i + \beta_x Experience_i + \beta_{x2} Experience^2 + \beta_s Skill_i + \beta_{sr} Skill \times D_r + \beta_r D_r,$$

where $Wage_{ir}$ is the reported wage for individual i in region r, $Gender_i$ represents individual i's gender, $Experience_i$ is the years of work experience, and D_r is a regional dummy for region r. $Skill_i$ is a skill dummy based on an education threshold of highschool or college. The estimated value of $\beta_s + \beta_{sr}$ is then used as our measure for the log of the relative wage ratios of skilled to unskilled workers in year 1996 or 2006, denoted by $\ln(W_s/W_u)_{96}$ or $\ln(W_s/W_u)_{06}$, respectively. These skill premium measures depend on whether an education threshold to define $Skill_i$ is highshool or college. The skill premium based on a threshold of highschool education are used for the regressions in columns (1)-(4) of Table 5 or columns (1)-(4), (9)-(12) of Table 6 while we use a threshold of college education for the regressions in columns (5)-(8) of Tables 5-6 .

Distance to Port

Among all ports in Indonesia, there are two large ports, sixteen medium-sized ports and all other ports are either small or very small, according to the World Port Source. The 18 large or medium sized ports are chosen to be the main destinations for our constructed measure of transportation cost. Specifically, given these destinations, and taking the geographical features of Indonesia into consideration, we compute the least-cost path from the center of every region to its nearest port by ArcGIS. The calculation divides the entire country into cells of size 1 km^2. 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 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 region is approximated by the the accumulative cost along the optimal route from the center cell of the region. For each plant, the proxy for its transportation cost is the transportation cost of the region 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.

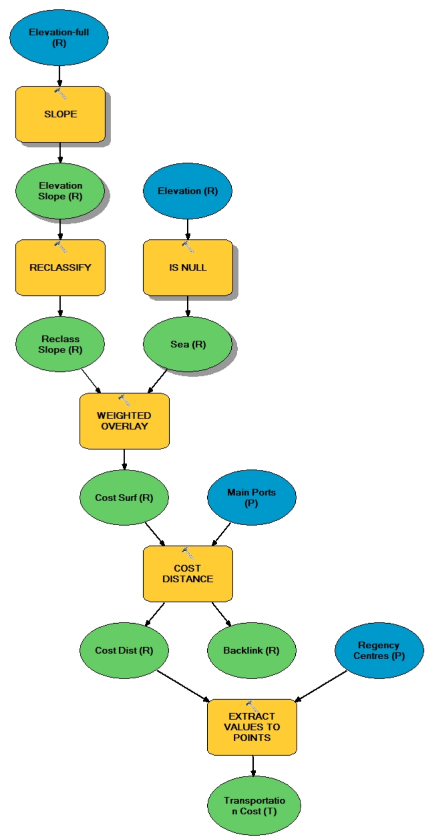
There are three main steps for computing the transportation cost. First, generate the cost raster for Indonesia which defines the cost to move planimetrically through each cell according to geographical features. Second, given a cost raster and the main ports as destination points, the "Cost Distance" 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 region, we extract the cost distance value for the cells located in the center of the regions 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 $Cost_i = 0.5 \times ReclassSlope_i + 0.5 \times 10^{Sea_i}$. 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.

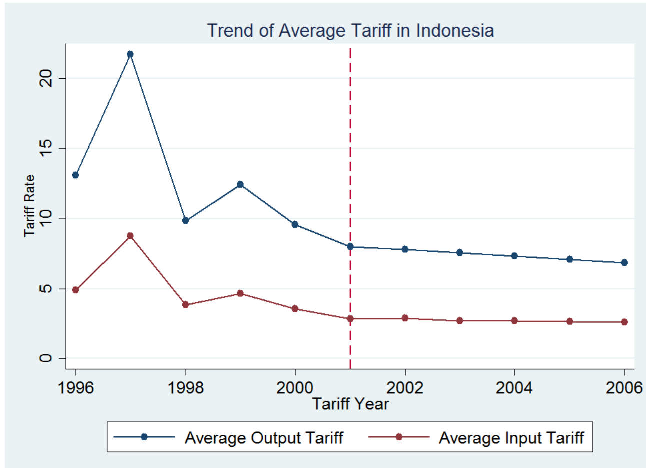
Step 3. We extract the values of the cells located in the center of administrative regencies from the transportation cost map "Cost Dist" using the tool "EXTRACT VALUES TO POINTS."

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.

Figure A.2: Trend of the Average Input and Output Tariff, 1996-2006



Notes: the industrial output tariffs are the effectively applied tariff provided by WITS. Industries are classified by 4-digit ISIC. The tariff of an industry is the simple average of the industry's tariffs charged to all trading countries.

A.3 Industrial Variables

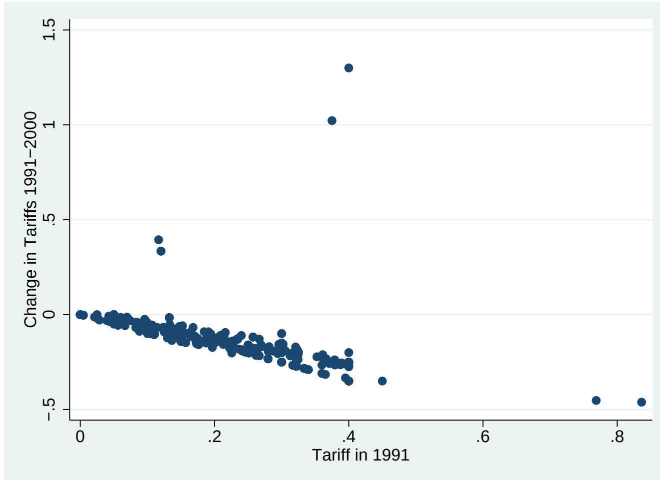
Tariffs

Tariff data are from Amiti and Konings (2007), where they constructed the input and output tariffs for 5-digit ISIC industries during 1996-2001 based on an input-output table that is not publicly available. We use the plants' 1996 industry affiliation to assign the tariff changes to individual plants. Using the initial industry affiliation prevents potential bias that would arise from plants which strategically switched to new industries in response to changes in the trade environment. One potential concern with this tariff data is that it does not cover the entire period we study (1996-2006). We use the tariff data from WITS that is reported at the 4-digit ISIC industry classification to check the tariff changes in the 2001-2006 period. Figure A.2 demonstrates that most of the reduction in Indonesian input and output tariffs occurred before 2001. 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. Given that most of the tariff reductions had occurred by 2001 and are driven by the initial tariff levels, we choose to use the tariff rates constructed by Amiti and Konings because they are constructed at a more disaggregated industry level, and thus provide more variation in the tariff changes across plants.

Import Heaviness and Airshare

This section describes our measures of the heaviness of imported inputs (import weight) and the fraction to of imported inputs shipped by air (import airshare) as described in the main text. We first create proxy variables for transport intensity at HS6 level for Indonesian imports using data on US and EU imports to Indonesia by mode of transportation for the year 2006. Detailed data for U.S. exports by commodity and transport mode are published by the US census at `http://www.census.gov/foreign-trade/reference/products/layouts/imdb.html#imp_detl`. Similar data for EU exports is taken from the EU International Trade Database ComExt which is published at `http://epp.eurostat.ec.europa.eu/newxtweb/`. The underlying data set for our EU instruments is collected in the dataset named 'EXTRA EU Trade Since 2000 By Mode of Transport (HS6) (DS-043328).' We then follow Cosar and Demir (2015)

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).

to construct the heaviness and fraction of imports shipped to Indonesia at each HS6 commodity code for both the EU and US series separately.

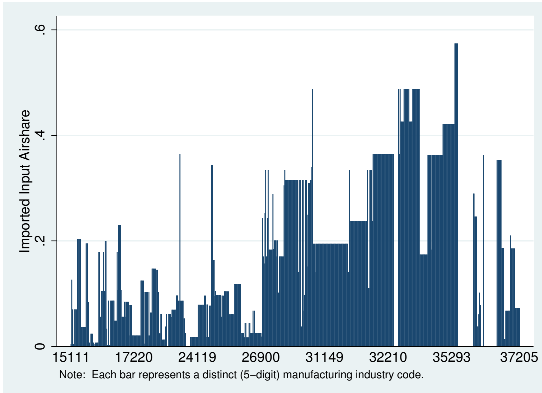
To create the measures of imported input heaviness and airshare we need to map the HS6 measures above to the import input-output matrix produced by BPS Indonesia. A key intermediate step in this process is linking the HS6 commodity codes to ISIC 3.0 industry classification in order to create industry-level import variables. To complete this task we use the correspondence table '2002_NAICS_to_ISIC_3.1' as published by the U.S. Census (`https://www.census.gov/cgi-bin/sssd/naics`) and the correspondence table 'isic31_to_isic3' from the United Nations Stats Division published online at `http://unstats.un.org/unsd/cr/registry/regot.asp?Lg=1`. For robustness, we repeat this concordance using the correspondence tables '2002_NAICS_to_ISIC_4', 'isic4_to_isic31' and 'isic31_to_isic3'. These produce similar results.

Last, we use the import Input-Output Table produced by BPS Indonesia (2000) to construct the imported input measures of heaviness and airshare. The input-output matrix provided by BPS Indonesia allows us to determine the share of import expenditures in each sector. Specifically, we subtract total domestic expenditures in any given sector from total expenditures in the same sector. For each sector we can then straightforwardly compute the share of total expenditures on imports from each individual sector.

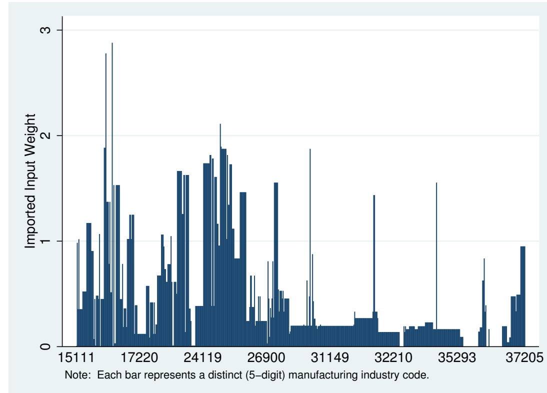
The input-output tables also provide a concordance between ISIC 3.0 classifications and Indonesian IO sectors. The IO tables are comprised 175 distinct 'sectors' which typically aggregate several ISIC 3.0 classifications. To determine the sectoral heaviness or airshare, we assign equal shares to all ISIC 3.0 classifications assigned to the same sector. As described in the main text, we then use the sectoral import expenditures shares to construct a measure imported input weight and airshare.

Figure 1 documents the variation in the fraction imports shipped by air and differences in the weight of imported inputs across industries. It is clear that there exist substantial differences across industries and, not surprisingly, industries which tend to import lighter inputs are also more likely to have them shipped by air, where the correlation coefficient between these instruments is -0.4.

Figure A.4: Import Airshare and Weight Instruments Across Industries



(a) Fraction of Import Shipments by Air



(b) Weight of Import Shipments

B Estimating MTE and Treatment Effects

We estimate the MTE and treatment parameters following a procedure similar to that of Carneiro, Heckman, and Vytlacil (2011). Because the support of $P(Z)$ 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. Furthermore, 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 lagged dependent variable (e.g., $(L_s^p/(L_s^p + L_u^p))_{96}$) while it also contain 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 when we use the log of the skill ratios as the dependent variable.[2] Then,

$$E[S|X = x, P(Z) = p] = x'\gamma + p\tilde{x}'\delta + K(p), \quad \Delta^{MTE}(x,p) = \tilde{x}'\delta + K'(p), \tag{11}$$

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.

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

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.

[2] In our preliminary investigation, when we estimated (11) by setting $\tilde{X}$ equal to all variables in X except for the local wage ratios, industry dummies, and province dummies, we found that the interaction terms with other variables in X were rarely significant across different specifications.

Table B.1: Estimates of Skill Demand Equation

Occupation Threshold	Production Highschool		Non-Production College		All Highschool		All College		All Occupation	
Dependent Var.	$(L_s^p/(L_u^p+L_s^p))_{06}$		$(L_s^n/(L_u^n+L_s^n))_{06}$		$(L_s/(L_u+L_s))_{06}$		$(L_s/(L_u+L_s))_{06}$		$(L^n/(L^n+L^p))_{06}$	
Export	-0.0298	[0.0255]	-0.0155	[0.0194]	-0.0306	[0.0265]	-0.0294	[0.0058]	-0.0322	[0.0126]
Capital	0.0218	[0.0060]	0.0020	[0.0045]	0.0194	[0.0058]	0.0012	[0.0012]	0.0022	[0.0029]
Hicks-neutral φ	0.0035	[0.0124]	0.0072	[0.0104]	0.0007	[0.0119]	-0.0010	[0.0028]	-0.0068	[0.0060]
Foreign	-0.0389	[0.0437]	-0.0211	[0.0404]	-0.0366	[0.0398]	-0.0158	[0.0120]	-0.0269	[0.0192]
R&D	0.0191	[0.0258]	0.0150	[0.0219]	0.0240	[0.0233]	0.0149	[0.0071]	0.0243	[0.0134]
Training	0.0370	[0.0178]	0.0208	[0.0129]	0.0312	[0.0179]	0.0059	[0.0039]	0.0064	[0.0072]
$\log(W_s/W_u)_{06}$	-0.0107	[0.0409]	-0.0112	[0.0320]	0.0077	[0.0422]	-0.0008	[0.0085]	0.0095	[0.0188]
$\log(W_s/W_u)_{96}$	-0.1482	[0.0527]	-0.0385	[0.0407]	-0.1511	[0.0521]	0.0040	[0.0111]	0.0232	[0.0206]
$(L_s^j/(L_u^p+L_s^j))_{06}$	0.0449	[0.0172]	0.1067	[0.0171]	-0.0328	[0.0267]	0.0207	[0.0040]	0.2414	[0.0367]
$(L_s^j/(L_u^p+L_s^j))_{06}\times P(Z)$	-0.5867	[0.1629]	-0.5345	[0.1694]	-0.4451	[0.2022]	0.0266	[0.0455]	0.1619	[0.1883]
No. Obs.	3997		3992		3985		3967		4000	

Notes: $j=n,p$. The bootstrap standard errors are in square brackets. Province dummies and 3-digit ISIC industry dummies are also included.

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.2 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 $\hat{P}(Z)$.

Table B.1 reports the estimates of the skill demand equation (11) using the sample of plants for which the estimated propensity scores are on the estimated common support when we use the share of skilled workers as the dependent variable. In the first three columns of Table B.1, the coefficient of the interaction term between the lagged dependent variable and the propensity score is negative and significant. 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 similar to those of the IV regressions in Tables 5-6.

As in 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 as follows:

$$\begin{aligned} ATE(x) &= \int_0^1 \Delta^{MTE}(x,p)dp, & TT(x) &= \int_0^1 \Delta^{MTE}(x,p)h_{TT}(x,p)dp, \\ TUT(x) &= \int_0^1 \Delta^{MTE}(x,p)h_{TUT}(x,p)dp, & PRTE(x) &= \int_0^1 \Delta^{MTE}(x,p)h_{PRTE}(x,p)dp, \qquad (12) \\ MPRTE(x) &= \int_0^1 \Delta^{MTE}(x,p)h_{PRTE}(x,p)dp, \end{aligned}$$

where

$$
\begin{aligned}
&h_{TT}(x,p) = \frac{1-F_P(p|X=x)}{E(P|X=x)}, \quad h_{TUT}(x,p) = \frac{F_P(p|X=x)}{E(1-P|X=x)},\\
&h_{PRTE}(x,p) = \frac{F_{P^*}(p|X=x) - F_P(p|X=x)}{E(P|X=x) - E(P^*|X=x)},\\
&h_{MPRTE}(x,p) = \lim_{\alpha\to 0} \frac{F_{P^*_\alpha}(p|X=x) - F_P(p|X=x)}{E(P|X=x) - E(P^*_\alpha|X=x)} = \frac{(\partial/\partial\alpha)F_{P^*_\alpha}(p|X=x)|_{\alpha=0}}{\int(\partial/\partial\alpha)F_{P^*_\alpha}(p|X=x)|_{\alpha=0}dp}.
\end{aligned} \tag{13}
$$

$F_P(\cdot|X=x)$ 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 (12) 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 (13) 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 (12) 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 three rows of Table B.2 report the bandwidth choices associated with estimating $f_P(p|x'\theta)$ and $f_{X'\theta}(x'\theta)$. Figure 4 shows estimated weights for ATE, TT, TUT, MPRTEs, and PRTE when dependent variable is $\ln(L_s^p/L_u^p)$.

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. When the value of P^* is above the maximum value of the support, the maximum value of P^* is set to the maximum value of the restricted support.

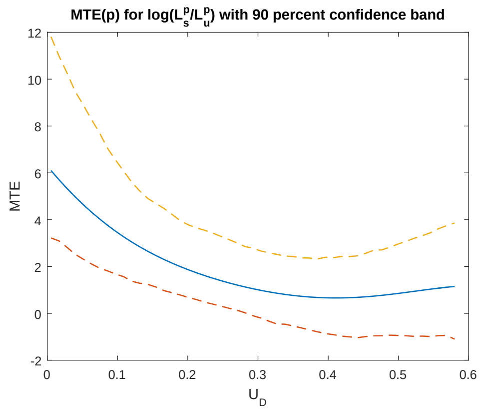
We use 500 bootstrap replications to construct equal-tailed bootstrap confidence bands for $\hat{\Delta}^{MTE}(x'\theta,p)$ and the standard errors for treatment effects. In each bootstrap iteration we re-estimate $P(Z)$ so all standard errors account for the fact that $P(Z)$ is estimated.

C Estimating Hicks-Neutral Productivity

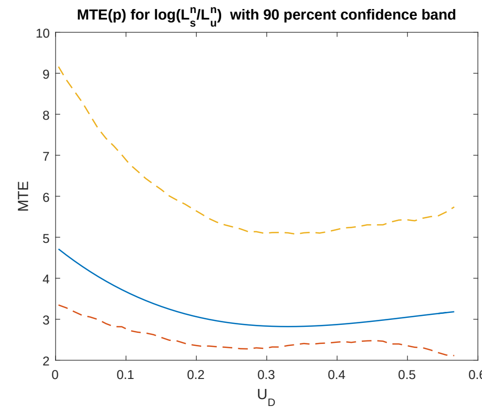
Our model implies that Hicks-neutral productivity differences are potentially among the most important determinants of plant-level import decisions. Unfortunately, the data do not provide a convenient measure of Hicks-neutral productivity. Moreover, standard productivity estimation methods do not consider how we might separately identify skill-biased and Hicks-neutral productivity.[3] Accordingly, we develop an

[3]Doraszelski and Jaumandreu (2014) is a key exception.

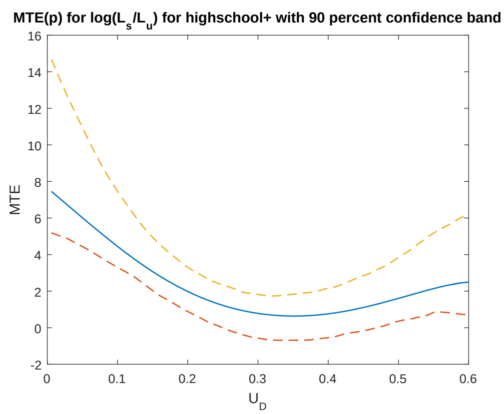
Figure B.5: Estimated MTE



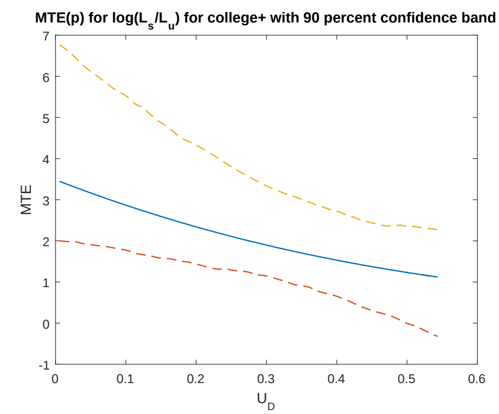
(a) Production, Highschool



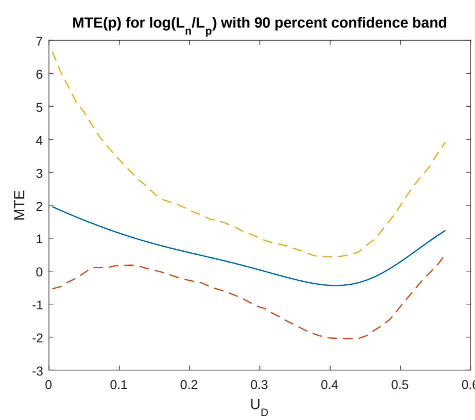
(b) Non-Production, College



(c) All, Highschool



(d) All, College



(e) All, Occupation

Table B.2: Bandwidth Choices by Cross-validation

Occupation Threshold	Production Highschool		Non-Production College	
Dependent Var.	$\ln\left(\frac{L_s^p}{L_u^p}\right)_{06}$ (1)	$\left(\frac{L_s^p}{L_u^p+L_s^p}\right)_{06}$ (2)	$\ln\left(\frac{L_s^n}{L_u^n}\right)_{06}$ (3)	$\left(\frac{L_s^n}{L_u^n+L_s^n}\right)_{06}$ (4)
Step 2: $E[S\|P]$	0.03	0.03	0.21	0.05
$E[\text{Export}\|P]$	0.03	0.05	0.07	0.05
$E[\text{Capital}\|P]$	0.05	0.01	0.03	0.03
$E[\varphi\|P]$	0.03	0.05	0.05	0.05
$E[\text{Foreign}\|P]$	0.42	0.03	0.33	0.43
$E[\text{R\&D}\|P]$	0.17	0.03	0.21	0.19
$E[\text{Training}\|P]$	0.03	0.05	0.05	0.05
$E[\ln(W_s/W_u)_{06}\|P]$	0.42	0.03	0.42	0.05
$E[\ln(W_s/W_u)_{96}\|P]$	0.07	0.01	0.11	0.03
$E[\ln(L_s^j/L_u^j)_{96}\|P]$	0.25	0.07		
$E[d_{u,96}^j\|P]$	0.42	0.01		
$E[d_{s,96}^j\|P]$	0.01	0.05		
$E[(L_s^j/(L_s^j+L_u^j)_{96}\|P]$			0.11	0.01
$E[\text{industry/province}\|P]^{(a)}$	0.03	0.03	0.09	0.03
Step 4: $E[S-X'\gamma-P(Z)\tilde{X}'\theta\|P]$	0.15	0.11	0.23	0.13
Bandwidth for P of $f_P(p\|x'\theta)$	0.01	0.01	0.01	0.01
Bandwidth for $X'\theta$ of $f_P(p\|x'\theta)$	0.01	0.02	0.02	0.01
Bandwidth for $f_{X'\theta}(x'\theta)$	0.02	0.03	0.04	0.02

Notes: $j = p, n$. 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.

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.[4]

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

$$Y_{it} = e^{\varepsilon_{it}} Q_{it}, \quad \text{where} \quad Q_{it} = e^{\alpha_0+\omega_{it}} K_{it}^{\alpha_k} M_{it}^{\alpha_m} L_{p,it}^{\alpha_p} L_{n,it}^{\alpha_n} \tag{14}$$

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

$$L_{j,it} = \left((A_j L_{j,it}^s)^{\frac{\sigma_j-1}{\sigma_j}} + (L_{j,it}^u)^{\frac{\sigma_j-1}{\sigma_j}} \right)^{\frac{\sigma_j}{\sigma_j-1}} \quad \text{for } j = p, n. \tag{15}$$

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.[5] The first order conditions with respect

[4] Other important contributions to this literature include Wooldridge (2009), De Loecker (2011), De Loecker et al. (2012) and Doraszelski and Jaumandreu (2014).

[5] Our method is broadly based on the ideas contained in Gandhi, Navarro, and Rivers (2013), but our production function is specified using a simple Cobb-Douglas form with CES aggregators for production and non-production

Table B.3: Import Decision Model using Logit for the Sample of Production Workers

Outcome Variable	$\ln(L_s^p/L_u^p)$				$L_s^p/(L_s^p+L_u^p)$			
	Coeff.	S.E.	Ave. Deriv.	S.E.	Coeff.	S.E.	Ave. Deriv.	S.E.
TC	-0.4082	[0.1605]	-0.0275	[0.0107]	-0.5104	[0.1693]	-0.0346	[0.0115]
Air	0.3666	[0.1352]	0.3142	[0.1129]	0.4482	[0.1465]	0.3862	[0.1244]
Wgt	-0.0091	[0.1613]	-0.0007	[0.0127]	0.0682	[0.1519]	0.0055	[0.0121]
$TC \times \log(\frac{L_s^p}{L_u^p})_{96}$	0.0412	[0.1217]	0.0014	[0.0041]				
$TC \times d_{u,96}^p$	-0.0132	[0.2417]	-0.0046	[0.0816]				
$TC \times d_{s,96}^p$	-0.1476	[0.1350]	-0.0162	[0.0146]				
$Air \times \log(\frac{L_s^p}{L_u^p})_{96}$	0.2962	[0.1380]	0.0973	[0.0444]				
$Air \times d_{u,96}^p$	0.0415	[0.1216]	0.1054	[0.3048]				
$Air \times d_{s,96}^p$	-0.0683	[0.1779]	-0.0778	[0.1994]				
$Wgt \times \log(\frac{L_s^p}{L_u^p})_{96}$	0.141	[0.1751]	0.0049	[0.0060]				
$Wgt \times d_{u,96}^p$	0.0313	[0.1447]	0.0113	[0.0515]				
$Wgt \times d_{s,96}^p$	0.0526	[0.1954]	0.0046	[0.0167]				
$TC \times (L_s^p/(L_s^p+L_u^p))_{96}$					0.0407	[0.1586]	0.004	[0.0156]
$Air \times (L_s^p/(L_s^p+L_u^p))_{96}$					-0.2712	[0.1469]	-0.2989	[0.1605]
$Wgt \times (L_s^p/(L_s^p+L_u^p))_{96}$					-0.1838	[0.1726]	-0.0196	[0.0183]
Export	0.373	[0.0742]	0.0525	[0.0104]	0.3857	[0.0696]	0.0545	[0.0099]
Capital	0.4058	[0.0855]	0.0122	[0.0025]	0.4306	[0.0842]	0.013	[0.0026]
Hicks-neutral φ	0.147	[0.0756]	0.0139	[0.0071]	0.1522	[0.0754]	0.0145	[0.0072]
Foreign	0.1389	[0.0479]	0.0542	[0.0181]	0.1398	[0.0496]	0.0549	[0.0192]
R&D	0.0765	[0.0540]	0.0172	[0.0121]	0.0818	[0.0546]	0.0185	[0.0123]
Training	0.1858	[0.0739]	0.0221	[0.0087]	0.2087	[0.0793]	0.025	[0.0095]
$\log(\frac{W_s}{W_u})_{06}$	0.0403	[0.0866]	0.0127	[0.0271]	0.041	[0.0941]	0.013	[0.0298]
$\log(\frac{W_s}{W_u})_{96}$	0.0282	[0.0919]	0.0117	[0.0377]	0.0109	[0.0884]	0.0045	[0.0367]
$\log(\frac{L_s^p}{L_u^p})_{96}$	-0.2394	[0.2104]	-0.0097	[0.0084]				
$d_{u,96}^p$	0.0276	[0.2414]	0.0115	[0.0996]				
$d_{s,96}^p$	0.0479	[0.2828]	0.0057	[0.0329]				
$(L_s^p/(L_s^p+L_u^p))_{96}$					0.1916	[0.2243]	0.0276	[0.0321]
No. Obs.	4064				4064			

Notes: Estimates are 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. 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.

to $L^u_{j,it}$ and $L^s_{j,it}$ are given by

$$\frac{W^u_t L^u_{j,it}}{Q_{it}} = \alpha_j \frac{(L^u_{j,it})^{\frac{\sigma_j-1}{\sigma_j}}}{(A_j L^s_{j,it})^{\frac{\sigma_j-1}{\sigma_j}} + (L^u_{j,it})^{\frac{\sigma_j-1}{\sigma_j}}} \quad \text{and} \quad \frac{W^s_t L^s_{j,it}}{Q_{it}} = \alpha_j \frac{(A_j L^s_{j,it})^{\frac{\sigma_j-1}{\sigma_j}}}{(A_j L^s_{j,it})^{\frac{\sigma_j-1}{\sigma_j}} + (L^u_{j,it})^{\frac{\sigma_j-1}{\sigma_j}}}, \tag{16}$$

respectively, so that

$$\left(\frac{L^u_{j,it}}{L^s_{j,it}}\right)^{\frac{1}{\sigma}} A_j^{\frac{\sigma_j-1}{\sigma_j}} = \frac{W^s_t}{W^u_t} \quad \text{for } j = p, n, \tag{17}$$

where W^s_t and W^u_t 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^s_t, and W^u_t. Substituting (17) into (15), we get

$$L_{j,it} = X_{j,it}^{-\frac{\sigma_j}{\sigma_j-1}} L^u_{j,it}, \quad \text{where} \quad X_{j,it} \equiv \frac{W^u_t L^u_{j,it}}{W^s_t L^s_{j,it} + W^u_t L^u_{j,it}}.$$

Substituting the above equation for $L_{j,it}$ into (14) and taking the logarithm gives

$$y_{it} = \alpha_{0,t} + \alpha_k k_{it} + \alpha_m m_{it} + \alpha_p l^u_{p,it} + \beta_p x_{p,it} + \alpha_n l^u_{n,it} + \beta_n x_{n,it} + \omega_{it} + \epsilon_{it} \tag{18}$$

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 (18) conditional on (m_{it}, k_{it}), and subtracting it from (18) gives

$$\begin{aligned} y_{it} - E[y_{it}|m_{it}, k_{it}] \quad &= \quad \alpha_p\{l^u_{p,it} - E[l^u_{p,it}|m_{it}, k_{it}]\} + \beta_p\{x_{p,it} - E[x_{p,it}|m_{it}, k_{it}]\} \\ &\quad + \alpha_n\{l^u_{n,it} - E[l^u_{n,it}|m_{it}, k_{it}]\} + \beta_n\{x_{n,it} - E[x_{n,it}|m_{it}, k_{it}]\} + \epsilon_{it}. \end{aligned} \tag{19}$$

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 (19) using the estimate of the conditional expectation terms. Note that, even though we consider the possibility of endogenous plant exit, 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 (18) as

$$\begin{aligned} x_{it} \quad &= \quad \alpha_{0,t} + \alpha_k k_{it} + \alpha_m m_{it} + E[\omega_{it}|\omega_{it-1}, \chi_{it} = 1] + \xi_{it} + \epsilon_{it} \\ &= \quad \alpha_k k_{it} + \alpha_m m_{it} + g_t(\underline{\omega}_t(k_{it}), \omega_{it-1}) + \xi_{it} + \epsilon_{it} \end{aligned} \tag{20}$$

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

labor inputs so that our analysis is substantially simpler than theirs.

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

$$\begin{aligned}
\Pr\{\chi_{it}=1|\omega_{it-1},k_{it-1},m_{it-1}\} &= \Pr\{\omega_t \geq \underline{\omega}_t(k_{it})|\omega_{it-1},m_{it-1},k_{it-1}\} \\
&= \int_{\underline{\omega}_t(k_{it}(m_{it-1},k_{it-1}))}^{\infty} F(d\omega_{it}|\omega^*_{t-1}(m_{it-1},k_{it-1})) \\
&= P^{\chi}_{it}. \qquad (21)
\end{aligned}$$

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, 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 (21). We estimate the survival probability (21) 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 (21) 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 (20) 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 (20) 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

$$x_{it}=\alpha_k k_{it}+\alpha_m m_{it}+q_t(P^{\chi}_t,h_{it-1})+\xi_{it}+\epsilon_{it}, \qquad (22)$$

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 $(\hat{\alpha}_p,\hat{\alpha}_n,\hat{\beta}_p,\hat{\beta}_n)$ are the first stage estimates of the 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 for 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 long differences.

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

$$Y_{it} = e^{\varepsilon_{it}} Q_{it}, \quad \text{where} \quad Q_{it} = e^{\alpha_0 + \omega_{it}} K_{it}^{\alpha_k} M_{it}^{\alpha_m} \tilde{L}_{p,it}^{\alpha_p} \tilde{L}_{n,it}^{\alpha_n} \tag{23}$$

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 First Differences, IV and Bias

This following derivations are an extension of Section 5.4 of Angrist and Pischke (2008). Consider a setting where β is constant parameter and that the data are generated from

$$Y_{it} = \alpha + \rho Y_{it-1} + \beta D_{it} + \epsilon_{it},$$

where $E[D_{it}\epsilon_{it}] \neq 0$ and $E[\epsilon_{it}|Z_{it}] = 0$ so that we may consistently estimate β by instrumental variable regression. Suppose that we mistakenly estimate a first-differenced equation using Z_{it} as IV using the sample of initial non-importers so that so that $D_{it} - D_{it-1} = D_{it}$ for every observation in the sample. The first-differenced IV estimator will converge in probability to $\frac{Cov(Y_{it}-Y_{it-1}, Z_{it})}{Cov(D_{it}, Z_{it})}$. Because $Y_{it} - Y_{it-1} = \alpha + (\rho - 1)Y_{it-1} + \beta D_{it} + \epsilon_{it}$,

$$\frac{Cov(Y_{it} - Y_{it-1}, Z_{it})}{Cov(D_{it}, Z_{it})} = \beta - (1-\rho)\frac{Cov(Y_{it-1}, Z_{it})}{Cov(D_{it}, Z_{it})}.$$

For our transport cost instrument, Z, we can empirically confirm that $\frac{Cov(Y_{it-1}, Z_{it})}{Cov(D_{it}, Z_{it})} > 0$ since $Cov(Y_{it-1}, Z_{it}) < 0$ and $Cov(D_{it}, Z_{it}) < 0$. Given that ρ is consistently estimated to lie between 0 and 1 in Tables 5 and 6 we expect that the β estimated in the first differenced IV regressions in Table 7 will be biased downwards.

E Capital-Skill Complementarity

We first extend our model in Section XX to include capital-skill complementarity by considering the following production function: $f(K, M, L_s, L_u, A, \varphi) = \varphi(V^p)^{\alpha_p}(V^n)^{\alpha_n} M^{\alpha_m}$, where φ is the firm's Hicks-Neutral productivity shock while V^j is a CES aggregator given by $V^j = [(A_j(L^j_s)^{\beta}(K^j)^{1-\beta})^{1/\rho_j} + (L^j_u)^{1/\rho_j}]^{\rho_j}$ with $\rho_j = \sigma_j/(\sigma_j - 1)$ for $j = \{n, p\}$. As before, A^j captures skill-biased technological change as in our benchmark model. However, in this case, it augments both skilled labor, L^j_s, and capital, K^j through the composite input $(L^j_s)^{\beta}(K^j)^{1-\beta}$. Minimizing the firm's costs, the relative demand for skilled labor can be written as:

$$\frac{L^j_s}{L^j_u} = \left(\beta\frac{W_u}{W_s}\right)^{\sigma_j} (A^j)^{\sigma_j - 1} \left(\frac{K^j}{L^j_s}\right)^{(\sigma_j-1)(1-\beta)}, \tag{24}$$

where we again assume that skill-biased technology is potentially a function of the firm's import decision as written in equation (2).

There are three issues here which merit comment. First, equation (24) demonstrates that if capital-skill complementarity is an important mechanism among Indonesian manufacturers our benchmark specification may potentially suffer from omitted variable bias. Second, the relative demand for skill equation (24) implies that we need to partition capital into production and non-production components (K^p and K^n). While the data do not provide a natural decomposition of capital across occupation, our model implies that we can decompose capital using the firm's first order conditions. Specifically, the firm's cost minimization problem implies that we can write the following relationships between capital and labor of each type:

$$K^p = \left(\frac{W_s}{W_k}\right)\left(\frac{1-\beta}{\beta}\right)L_s^p \quad \text{and} \quad K^n = \left(\frac{W_s}{W_k}\right)\left(\frac{1-\beta}{\beta}\right)L_s^n.$$

Therefore, total capital is related to total skilled labor as

$$K = K^n + K^p = \left(\frac{W_s}{W_k}\right)\left(\frac{1-\beta}{\beta}\right)(L_s^p + L_s^n), \tag{25}$$

and it follows that the fraction of total capital allocated to occupation $j \in \{n, p\}$ can be determined by dividing K^n or K^p by equation (25) as

$$\frac{K^j}{K} = \frac{L_s^j}{L_s^j + L_u^j}.$$

Note that this result is sensitive to the assumption that the share of skilled labor and capital, β, is equal across occupations. However, the alternative assumption that β varies across occupations but capital is allocated in a fashion such that each firm has the same ratio of production to non-production capital (i.e., $K^n = \gamma K$ and $K^p = (1-\gamma)K$ for some $\gamma \in (0,1)$) results in a nearly identical empirical structure. We do not find any significant difference using this alternative assumption and, as such, we omit further discussion hereafter.

Finally, it is clear that capital-skill complementarity implies adding one additional variable to our benchmark empirical specification, the log ratio of capital to total (production and non-production) skilled labor, $\ln(K/(L_s^p + L_s^n))$. As noted in the main text, when including the endogenous capital-skill control variable we also use lagged (i.e., 1996) values of $\ln(K/(L_s^p + L_s^n))$ as an additional instrument along with interactions of $\ln(K/(L_s^p + L_s^n))$ with our benchmark instruments.

F Investigating Differences with Amiti and Cameron (2012)

Column 1 of Table F.5 is our best replication of column 2 of Table 8 in Amiti and Cameron (2012). In this exercise we regress $\textit{Relative education intensity}_{f,i,2006}$ as defined in Amiti and Cameron (2012) on import and export dummies in 2006 and include all plants in the balanced panel. Although we are unable to exactly match the Amiti and Cameron result of a negative and significant coefficient on import status, we do estimate a negative import coefficient which is consistent with their findings.

In column (2) we repeat the exercise, but replace import and export status with the change in import and export status. In this case, we estimate a *positive* and significant coefficient on the change in import status. One possible interpretation of this positive correlation between the change in relative education intensity and the change in import status in column (2) is that starting to import induces more education-upgrading within production workers than within non-production workers.

Table F.4: Investigating Differences with Amiti and Cameron (2012)

Dependent Var.	Δ Relative Education Intensity (1996-2006)	
	(1)	(2)
Import Status	-0.027	
	(0.026)	
Export Status	-0.099***	
	(0.026)	
Import Status$_{96}$	-0.099***	
	(0.028)	
Δ Import Status		0.058**
		(0.024)
Δ Export Status		0.006
		(0.023)
Industry FE	Yes	Yes
No. Obs	7,192	7,192
R^2	0.085	0.083

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors are in square brackets. Column (1) replicates column (2) of Table 8 in Amiti and Cameron (2012) using import status in 2006. Column (2) considers a specification where we replace import and export status with the change in import and export status.

Table G.5: A Decomposition of Plant-Level Skill Growth by Import Status

Panel A: Skilled Workers, Highschool+						
	All		Initial Non-importers			
			switchers		non-switchers	
	1996	2006	1996	2006	1996	2006
Levels						
L_s/L	0.3221	0.4667	0.4115	0.5751	0.2588	0.4013
L_s^p/L^p	0.2749	0.4234	0.3666	0.5381	0.2117	0.3569
L_s^n/L^n	0.6846	0.7629	0.7281	0.7885	0.6518	0.7315
L^n/L	0.1646	0.1687	0.1684	0.1912	0.1495	0.1543
Decomposition of the overall changes						
$\Delta(L_s/L)$	0.1446		0.1636		0.1425	
within prod.	0.1248		0.1409		0.1235	
within non-prod.	0.0137		0.0113		0.0128	
between	0.0060		0.0114		0.0062	
Obs.	10,537		658		7,464	
Panel B: Skilled Workers, College+						
	All		Initial Non-importers			
			switchers		non-switchers	
	1996	2006	1996	2006	1996	2006
Levels						
L_s/L	0.0325	0.0500	0.0458	0.0727	0.0219	0.0363
L_s^p/L^p	0.0134	0.0209	0.0221	0.0313	0.0081	0.0141
L_s^n/L^n	0.1376	0.1964	0.1750	0.2490	0.1096	0.1618
L^n/L	0.1646	0.1687	0.1684	0.1912	0.1495	0.1543
Decomposition of the overall changes						
$\Delta(L_s/L)$	0.0175		0.0270		0.0144	
within prod.	0.0058		0.0067		0.0048	
within non-prod.	0.0106		0.0147		0.0085	
between	0.0011		0.0056		0.0011	
Obs.	10,537		658		7,464	

[a.] Source: Indonesia Manufacturing Survey in 1996 and 2006.
[b.] Skilled workers are defined as workers with education no less than highschool in top panel and workers with no less than college in the bottom panel. Plants with no production workers in 1996 or 2006 are excluded (only three observations). Plants with no non-production worker in either period are treated as having zero within-non-production changes, and the mean value of skill share in non-production sector $(\overline{L_s^n/L^n})$ is computed using the period when the number of non-production workers is positive. Plants with no non-production workers in both 1990 and 2006 simply have a zero within non-production component and zero between component.

G Additional Tables

Table G.6: Robustness Checks: Skill Threshold Definitions

Occupation	Production				Non-Production			
Threshold	College				Highschool			
Dependent Variable	$\ln(L_s^p/L_u^p)$		$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$		$\ln(L_s^n/L_u^n)$		$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Status	0.262**	4.471*	0.011**	0.068**	0.213*	2.434**	-0.028	0.582**
	[0.133]	[2.588]	[0.005]	[0.035]	[0.127]	[1.019]	[0.018]	[0.253]
Export Status	-0.364***	-0.668***	-0.008***	-0.012***	0.051	-0.123	0.019	-0.029
	[0.098]	[0.229]	[0.002]	[0.004]	[0.095]	[0.135]	[0.013]	[0.026]
Wage_{06}^j	-0.210	-0.757**	-0.001	-0.001	-0.044	-0.069	0.079**	0.073*
	[0.157]	[0.367]	[0.002]	[0.002]	[0.210]	[0.222]	[0.036]	[0.039]
Capital	-0.038	-0.150*	0.003***	0.002***	0.116***	0.075**	0.015***	0.006
	[0.027]	[0.078]	[0.001]	[0.001]	[0.021]	[0.032]	[0.003]	[0.005]
Hicks-neutral, φ	-0.073	-0.173	0.003**	0.002	-0.161***	-0.221***	0.010	-0.000
	[0.060]	[0.106]	[0.001]	[0.001]	[0.055]	[0.062]	[0.009]	[0.011]
Foreign-Owned	0.121	-0.815	0.003	-0.004	0.236	-0.120	0.006	-0.075
	[0.195]	[0.639]	[0.007]	[0.008]	[0.197]	[0.259]	[0.028]	[0.049]
R&D	0.232**	0.098	0.012***	0.010**	0.253**	0.064	0.004	-0.032
	[0.109]	[0.199]	[0.004]	[0.004]	[0.126]	[0.163]	[0.018]	[0.025]
Training	-0.168**	-0.255*	0.009***	0.007***	0.133*	0.132	0.008	-0.009
	[0.084]	[0.139]	[0.002]	[0.002]	[0.077]	[0.086]	[0.012]	[0.015]
Wage_{96}^j	0.361**	0.270	0.006**	0.005	-0.310	-0.335	-0.091**	-0.094**
	[0.171]	[0.273]	[0.003]	[0.003]	[0.240]	[0.253]	[0.038]	[0.043]
$\ln(L_s^j/L_u^j)_{96}$	0.244***	0.124			0.319***	0.286***		
	[0.047]	[0.105]			[0.036]	[0.039]		
d_u^j					0.239***	0.218***		
					[0.064]	[0.069]		
d_s^j	-0.906***	-0.313			-0.384***	-0.392***		
	[0.184]	[0.478]			[0.086]	[0.089]		
$\left(\frac{L_s^j}{L_s^j+L_u^j}\right)_{96}$			0.096***	0.077**			0.210***	0.211***
			[0.032]	[0.034]			[0.017]	[0.018]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.314	—	0.111	—	0.255	—	0.167	—
Hansen J p-value	—	0.252	—	0.052	—	0.337	—	0.366
No. Obs	959	947	4,445	4,410	1,631	1,619	4,021	3,988

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. The education threshold used to determine a skilled production worker is a college degree, while the threshold used for a skilled non-production worker is a highschool diploma. Import status is treated as an endogenous variable in columns (2), (4), (6) and (8). It is instrumented with both the distance to port and the share of imports shipped by air. The variable d_u^p is dropped from regressions (1) and (2) due to collinearity (It takes the same value in 99.999 percent of all observations using the college threshold as a definition of skill).

Table G.7: First Stage Results: Import Status

Occupation Threshold	Production Highschool		Non-Production College		All Highschool		All College		All Occupation	
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)	OLS (9)	OLS (10)
Distance to Port	-0.031***	-0.031***	-0.029***	-0.030***	-0.027***	-0.031***	-0.035***	-0.030***	-0.032***	-0.032***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.008]	[0.013]	[0.008]	[0.008]	[0.008]
Import Airshare	0.399***	0.404***	0.388***	0.440***	0.401**	0.399***	0.677***	0.393***	0.447***	0.411***
	[0.143]	[0.143]	[0.144]	[0.153]	[0.159]	[0.143]	[0.232]	[0.143]	[0.153]	[0.144]
Export Status	0.084***	0.082***	0.084***	0.082***	0.085***	0.083***	0.103***	0.084***	0.084***	0.083***
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.019]	[0.014]	[0.014]	[0.014]
Wage^j_{06}	0.019	0.019			0.030	0.018			0.019	0.021
	[0.019]	[0.019]			[0.022]	[0.019]			[0.021]	[0.019]
Capital	0.014***	0.013***	0.014***	0.015***	0.016***	0.013***	0.021***	0.014***	0.016***	0.015***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]
Hicks-neutral, φ	0.011	0.010	0.012	0.012	0.011	0.010	0.015	0.011	0.013	0.011
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.011]	[0.008]	[0.008]	[0.008]
Foreign-Owned	0.122***	0.124***	0.121***	0.126***	0.123***	0.125***	0.153***	0.122***	0.130***	0.126***
	[0.041]	[0.041]	[0.041]	[0.042]	[0.042]	[0.041]	[0.049]	[0.041]	[0.042]	[0.042]
R&D	0.046**	0.045**	0.047**	0.048**	0.048**	0.046**	0.042	0.045**	0.050**	0.049**
	[0.022]	[0.022]	[0.022]	[0.023]	[0.023]	[0.022]	[0.027]	[0.023]	[0.023]	[0.022]
Training	0.028***	0.026***	0.030***	0.029***	0.025**	0.027***	0.038**	0.029***	0.033***	0.031***
	[0.009]	[0.009]	[0.010]	[0.010]	[0.010]	[0.009]	[0.015]	[0.009]	[0.010]	[0.009]
Wage^j_{96}	0.036	0.038	0.002	-0.006	0.035	0.038	0.015	0.001	0.036	0.036
	[0.028]	[0.028]	[0.019]	[0.021]	[0.032]	[0.028]	[0.036]	[0.019]	[0.031]	[0.028]
$\ln(L^j_s/L^j_u)_{96}$	0.008**		0.013**		0.008**		0.015**			
	[0.004]		[0.006]		[0.004]		[0.007]			
d^j_u	0.075*		-0.010		-0.002		-0.033			
	[0.040]		[0.009]		[0.008]		[0.028]			
d^j_s	-0.008		-0.025**		0.011		0.007			
	[0.009]		[0.012]		[0.009]		[0.018]			
$\left(\frac{L^j_s}{L^j_s+L^j_u}\right)_{96}$		0.054***		0.031		0.047**		0.191*		
		[0.019]		[0.024]		[0.019]		[0.099]		
$\ln(L^n/L^p)_{96}$									-0.005	
									[0.004]	
d^p									0.012	
									[0.008]	
d^n									0.009	
									[0.009]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										-0.030
										[0.023]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat Exc. IVs.	11.75	11.83	10.73	10.38	8.04	11.58	8.23	11.16	11.35	12.62
No. Obs	4,410	4,410	4,410	3,988	3,756	4,410	2,004	4,410	3,988	4,410

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions.

Table G.8: First Stage Results: Export Status

Occupation Threshold	Production Highschool		Non-Production College		All Highschool		All College		All Occupation	
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distance to Port	0.001	0.001	0.002	-0.005	-0.007	0.002	-0.017	0.000	-0.010	-0.001
	[0.014]	[0.014]	[0.013]	[0.014]	[0.015]	[0.014]	[0.023]	[0.013]	[0.014]	[0.014]
Import Airshare	-0.770***	-0.767***	-0.777***	-0.745***	-0.740***	-0.774***	-0.603*	-0.740***	-0.712***	-0.735***
	[0.203]	[0.202]	[0.202]	[0.216]	[0.225]	[0.203]	[0.330]	[0.205]	[0.212]	[0.205]
Δ Output Tariff	-0.005***	-0.005***	-0.005***	-0.005***	-0.006***	-0.005***	-0.009***	-0.005***	-0.005***	-0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
Δ Market Access	-0.005	-0.005	-0.006*	-0.005	-0.005	-0.005	-0.008	-0.005	-0.005	-0.004
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.003]	[0.007]	[0.003]	[0.004]	[0.003]
Control Vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat Exc. IVs.	16.89	17.57	17.66	16.78	16.83	17.86	10.45	17.51	14.85	16.98
No. Obs	3,498	3,498	3,498	3,208	3,048	3,498	1,612	3,498	3,208	3,498

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions.

Table G.9: First Stage Results: Import Status, Large Instrument Set

Occupation Threshold	Production Highschool		Non-Production College		All Highschool		All College		All Occupation	
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distance to Port	-0.031***	-0.032***	-0.031***	-0.030***	-0.027***	-0.031***	-0.036***	-0.030***	-0.033***	-0.033***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.008]	[0.013]	[0.008]	[0.008]	[0.008]
Import Airshare	0.392***	0.393***	0.404***	0.438***	0.401**	0.388**	0.684***	0.380**	0.454***	0.403***
	[0.150]	[0.150]	[0.151]	[0.161]	[0.167]	[0.150]	[0.239]	[0.151]	[0.161]	[0.151]
Import Weight	-0.005	-0.005	-0.005	-0.007	-0.007	-0.004	-0.010	-0.004	-0.008	-0.004
	[0.008]	[0.008]	[0.008]	[0.009]	[0.009]	[0.008]	[0.016]	[0.008]	[0.009]	[0.008]
Δ Import Tariff	0.000	0.001	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Control Vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat Exc. IVs.	6.42	6.63	6.35	5.75	4.43	6.45	4.28	6.29	6.00	6.80
No. Obs	4,408	4,408	4,408	3,986	3,754	4,408	2,002	4,408	3,986	4,408

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions.

Table G.10: Robustness Check: Skill Supply Control

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dependent Variable	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	2.448*	0.778***	3.783***	0.513**	3.388**	0.660***	3.041**	0.226***	0.786	0.024
	[1.364]	[0.274]	[1.344]	[0.231]	[1.684]	[0.238]	[1.268]	[0.070]	[0.812]	[0.120]
Skill Supply$_{06}$	0.244***	0.050***	0.131**	0.017**	0.185***	0.053***	0.029	0.004*	0.035	0.003
	[0.070]	[0.012]	[0.061]	[0.008]	[0.065]	[0.011]	[0.059]	[0.002]	[0.039]	[0.006]
Export Status	-0.157	-0.035	-0.470***	-0.017	-0.202	-0.028	-0.509***	-0.025***	-0.165*	-0.016
	[0.128]	[0.027]	[0.168]	[0.023]	[0.159]	[0.024]	[0.157]	[0.007]	[0.087]	[0.012]
Wage$^j_{06}$	-0.452	-0.028	-0.282	-0.038	-0.368	-0.004	-0.198	-0.011*	0.024	0.000
	[0.333]	[0.034]	[0.231]	[0.024]	[0.313]	[0.031]	[0.187]	[0.006]	[0.120]	[0.015]
Capital	0.095***	0.014***	-0.071**	0.007	0.072**	0.013***	-0.033	0.002*	0.013	0.004*
	[0.029]	[0.005]	[0.036]	[0.005]	[0.034]	[0.004]	[0.037]	[0.001]	[0.017]	[0.002]
Hicks-neutral, φ	-0.314***	-0.020**	-0.058	0.022**	-0.254***	-0.022**	-0.047	0.001	-0.125***	-0.006
	[0.056]	[0.010]	[0.064]	[0.010]	[0.056]	[0.009]	[0.058]	[0.003]	[0.034]	[0.005]
Foreign-Owned	-0.035	-0.066	-0.291	-0.039	-0.145	-0.046	-0.366	-0.019	-0.160	-0.014
	[0.222]	[0.052]	[0.295]	[0.044]	[0.247]	[0.046]	[0.296]	[0.015]	[0.146]	[0.021]
R&D	-0.084	-0.001	-0.128	-0.001	0.040	0.005	0.030	0.013	0.144	0.026**
	[0.139]	[0.027]	[0.164]	[0.022]	[0.152]	[0.024]	[0.121]	[0.008]	[0.088]	[0.013]
Training	0.176**	0.034**	-0.077	0.032***	0.234***	0.033***	0.011	0.011***	0.049	0.013*
	[0.075]	[0.014]	[0.087]	[0.012]	[0.071]	[0.013]	[0.089]	[0.004]	[0.048]	[0.007]
Skill Supply$_{96}$	-0.006	-0.008	-0.075	0.009	0.019	-0.006	0.038	0.003	0.052	0.006
	[0.083]	[0.015]	[0.073]	[0.008]	[0.080]	[0.013]	[0.068]	[0.002]	[0.045]	[0.006]
$\ln(L_s/L_u)_{96}$	0.338***		0.123***		0.407***		0.316***			
	[0.027]		[0.034]		[0.031]		[0.044]			
d_u	0.070		0.125*		-0.081		-0.232			
	[0.237]		[0.070]		[0.055]		[0.182]			
d_s	-0.960***		0.107		0.022		0.097			
	[0.101]		[0.136]		[0.070]		[0.078]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.385***		0.160***		0.432***		0.229***		
		[0.029]		[0.028]		[0.025]		[0.047]		
$\ln(L^n/L^p)_{96}$									0.391***	
									[0.020]	
d^p									-0.116**	
									[0.036]	
d^n									0.082**	
									[0.033]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.363***
										[0.022]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.289	0.242	0.551	0.425	0.419	0.529	0.913	0.459	0.746	0.731
No. Obs	3,109	4,408	2,087	3,986	3,403	4,408	1,639	4,408	3,986	4,408

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.11: Robustness Check: Large Instrument Set

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dependent Variable	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	3.240***	0.864***	3.498***	0.672***	4.105***	0.818***	3.191***	0.267***	1.557**	0.116
	[1.247]	[0.254]	[1.049]	[0.230]	[1.496]	[0.235]	[1.072]	[0.069]	[0.746]	[0.108]
Export Status	-0.236*	-0.044*	-0.454***	-0.032	-0.265*	-0.044*	-0.532***	-0.029***	-0.235***	-0.025**
	[0.122]	[0.026]	[0.137]	[0.023]	[0.146]	[0.024]	[0.136]	[0.007]	[0.083]	[0.011]
Wage^j_{06}	-0.149	-0.014	-0.200	-0.026	-0.149	0.004	-0.175	-0.008	0.046	-0.001
	[0.184]	[0.027]	[0.145]	[0.019]	[0.166]	[0.026]	[0.141]	[0.005]	[0.106]	[0.014]
Capital	0.080***	0.013***	-0.067**	0.005	0.056*	0.011**	-0.039	0.002	0.001	0.003
	[0.028]	[0.005]	[0.030]	[0.005]	[0.031]	[0.004]	[0.033]	[0.001]	[0.016]	[0.002]
Hicks-neutral, φ	-0.306***	-0.019*	-0.042	0.020**	-0.252***	-0.022**	-0.048	0.000	-0.131***	-0.007
	[0.059]	[0.010]	[0.060]	[0.010]	[0.059]	[0.010]	[0.057]	[0.003]	[0.036]	[0.005]
Foreign-Owned	-0.194	-0.089*	-0.251	-0.063	-0.280	-0.077	-0.393	-0.025	-0.268*	-0.026
	[0.234]	[0.052]	[0.255]	[0.046]	[0.254]	[0.049]	[0.273]	[0.016]	[0.149]	[0.020]
R&D	-0.140	-0.008	-0.104	-0.009	-0.014	-0.006	0.026	0.011	0.097	0.021
	[0.142]	[0.028]	[0.149]	[0.024]	[0.154]	[0.026]	[0.121]	[0.009]	[0.091]	[0.013]
Training	0.140*	0.029**	-0.070	0.026**	0.212***	0.026*	0.001	0.010***	0.016	0.009
	[0.076]	[0.014]	[0.080]	[0.013]	[0.072]	[0.013]	[0.084]	[0.004]	[0.047]	[0.006]
Wage^j_{96}	-0.642***	-0.134***	0.186	0.013	-0.751***	-0.131***	0.226	0.012*	0.029	0.025
	[0.217]	[0.038]	[0.179]	[0.023]	[0.209]	[0.035]	[0.173]	[0.006]	[0.126]	[0.016]
$\ln(L_s/L_u)_{96}$	0.338***		0.127***		0.412***		0.314***			
	[0.028]		[0.032]		[0.032]		[0.043]			
d_u	0.070		0.136**		-0.063		-0.234			
	[0.251]		[0.068]		[0.058]		[0.183]			
d_s	-0.954***		0.078		0.026		0.105			
	[0.083]		[0.132]		[0.072]		[0.080]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.389***		0.164***		0.441***		0.227***		
		[0.029]		[0.030]		[0.027]		[0.049]		
$\ln(L^n/L^p)_{96}$									0.397***	
									[0.020]	
d^p									-0.132***	
									[0.038]	
d^n									0.080**	
									[0.035]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.368***
										[0.022]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.001	0.001	0.134	0.268	0.067	0.001	0.231	0.081	0.558	0.328
No. Obs	3,109	4,408	2,087	3,986	3,403	4,408	1,639	4,408	3,986	4,408

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.12: Robustness Check: Import Intensity

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dependent Variable	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	7.309*	1.640**	5.498	1.420**	8.128*	1.458**	3.825	0.445**	2.945	0.148
	[3.974]	[0.658]	[3.640]	[0.675]	[4.632]	[0.600]	[2.554]	[0.179]	[1.936]	[0.238]
Import Share	-8.143	-1.479	-2.563	-1.445	-7.487	-1.200	-0.715	-0.354	-3.417	-0.116
	[8.230]	[1.365]	[6.897]	[1.323]	[8.824]	[1.233]	[3.979]	[0.375]	[3.768]	[0.475]
Export Status	-0.288*	-0.066**	-0.566***	-0.053*	-0.387*	-0.062**	-0.569***	-0.033***	-0.216**	-0.021*
	[0.151]	[0.032]	[0.161]	[0.030]	[0.207]	[0.030]	[0.160]	[0.009]	[0.094]	[0.012]
Wage^j_{06}	-0.452	-0.028	-0.282	-0.038	-0.368	-0.004	-0.198	-0.011*	0.024	0.000
	[0.333]	[0.034]	[0.231]	[0.024]	[0.313]	[0.031]	[0.187]	[0.006]	[0.120]	[0.015]
Capital	0.064*	0.010*	-0.089**	0.001	0.035	0.008	-0.048	0.001	-0.002	0.003
	[0.036]	[0.006]	[0.040]	[0.006]	[0.041]	[0.005]	[0.037]	[0.002]	[0.019]	[0.002]
Hicks-neutral, φ	-0.392***	-0.032**	-0.090	0.015	-0.352***	-0.035***	-0.041	-0.001	-0.146***	-0.008
	[0.090]	[0.015]	[0.085]	[0.014]	[0.091]	[0.014]	[0.081]	[0.004]	[0.046]	[0.006]
Foreign-Owned	-0.451	-0.123*	-0.403	-0.100	-0.582	-0.107	-0.538	-0.034*	-0.300	-0.026
	[0.433]	[0.074]	[0.345]	[0.065]	[0.428]	[0.067]	[0.373]	[0.020]	[0.190]	[0.023]
R&D	-0.198	-0.020	-0.198	-0.020	-0.115	-0.017	-0.005	0.009	0.110	0.023*
	[0.194]	[0.037]	[0.195]	[0.033]	[0.219]	[0.033]	[0.135]	[0.011]	[0.103]	[0.013]
Training	0.104	0.026	-0.098	0.022	0.184*	0.022	-0.025	0.008*	0.014	0.009
	[0.101]	[0.018]	[0.103]	[0.017]	[0.097]	[0.016]	[0.119]	[0.005]	[0.053]	[0.007]
Wage^j_{96}	-0.757***	-0.180***	0.114	-0.001	-0.919***	-0.169***	0.203	0.008	-0.055	0.023
	[0.275]	[0.053]	[0.253]	[0.033]	[0.283]	[0.049]	[0.195]	[0.008]	[0.160]	[0.019]
$\ln(L_s/L_u)_{96}$	0.321***		0.116***		0.391***		0.298***			
	[0.039]		[0.037]		[0.045]		[0.061]			
d_u	0.148		0.151*		-0.063		-0.169			
	[0.340]		[0.082]		[0.071]		[0.201]			
d_s	-0.966***		0.044		-0.057		0.103			
	[0.101]		[0.154]		[0.104]		[0.087]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.381***		0.142***		0.439***		0.203***		
		[0.037]		[0.042]		[0.033]		[0.060]		
$\ln(L^n/L^p)_{96}$									0.398***	
									[0.022]	
d^p									-0.141***	
									[0.042]	
d^n									0.079**	
									[0.039]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.370***
										[0.022]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs	3,024	4,287	2,038	3,876	3,308	4,287	1,604	4,287	3,876	4,287

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.13: Robustness Check: TFP Measurement

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dependent Variable	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	3.151***	0.947***	3.885***	0.724***	3.968***	0.885***	3.264***	0.275***	1.226*	0.089
	[1.211]	[0.270]	[1.133]	[0.238]	[1.451]	[0.248]	[1.072]	[0.071]	[0.729]	[0.105]
Export Status	-0.255**	-0.051*	-0.495***	-0.033	-0.276*	-0.051**	-0.537***	-0.029***	-0.223***	-0.023**
	[0.121]	[0.027]	[0.147]	[0.024]	[0.143]	[0.025]	[0.137]	[0.007]	[0.082]	[0.011]
Wage^j_{06}	-0.108	-0.014	-0.209	-0.027	-0.119	0.005	-0.171	-0.008	0.056	-0.001
	[0.183]	[0.028]	[0.150]	[0.019]	[0.164]	[0.026]	[0.141]	[0.005]	[0.104]	[0.014]
Capital	0.055**	0.011**	-0.078**	0.006	0.041	0.009*	-0.044	0.002	-0.004	0.003
	[0.028]	[0.005]	[0.034]	[0.005]	[0.031]	[0.005]	[0.034]	[0.001]	[0.016]	[0.002]
Solow Residual	0.001	0.011	0.023	0.014	0.022	0.008	0.031	0.003	-0.032	-0.000
	[0.044]	[0.009]	[0.050]	[0.008]	[0.046]	[0.008]	[0.048]	[0.002]	[0.027]	[0.004]
Foreign-Owned	-0.240	-0.104*	-0.315	-0.068	-0.317	-0.090*	-0.413	-0.027*	-0.244*	-0.024
	[0.233]	[0.056]	[0.273]	[0.048]	[0.250]	[0.052]	[0.275]	[0.016]	[0.144]	[0.020]
R&D	-0.180	-0.016	-0.141	-0.009	-0.051	-0.014	0.011	0.010	0.097	0.021
	[0.142]	[0.030]	[0.159]	[0.025]	[0.152]	[0.027]	[0.123]	[0.009]	[0.088]	[0.013]
Training	0.114	0.025*	-0.086	0.026**	0.192***	0.022	-0.008	0.010**	0.016	0.009
	[0.076]	[0.015]	[0.084]	[0.013]	[0.071]	[0.014]	[0.085]	[0.004]	[0.047]	[0.006]
Wage^j_{96}	-0.644***	-0.137***	0.168	0.011	-0.743***	-0.133***	0.220	0.011*	0.045	0.026*
	[0.216]	[0.040]	[0.188]	[0.023]	[0.207]	[0.037]	[0.175]	[0.006]	[0.123]	[0.016]
$\ln(L_s/L_u)_{96}$	0.340***		0.126***		0.412***		0.314***			
	[0.027]		[0.033]		[0.031]		[0.043]			
d_u	0.076		0.134*		-0.053		-0.233			
	[0.249]		[0.071]		[0.057]		[0.186]			
d_s	-0.944***		0.081		0.031		0.104			
	[0.083]		[0.137]		[0.071]		[0.081]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.384***		0.163***		0.435***		0.225***		
		[0.031]		[0.031]		[0.028]		[0.050]		
$\ln(L^n/L^p)_{96}$									0.395***	
									[0.020]	
d^p									-0.123***	
									[0.037]	
d^n									0.088**	
									[0.034]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.367***
										[0.022]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.087	0.107	0.519	0.184	0.157	0.154	0.777	0.229	0.327	0.834
No. Obs	3,112	4,411	2,090	3,989	3,406	4,411	1,642	4,411	3,989	4,411

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.14: Robustness Check: Instrumenting Export Status

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dependent Variable	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	2.977**	0.909***	4.240**	0.888***	4.446**	0.947***	0.933	0.191**	0.739	0.014
	[1.289]	[0.305]	[1.701]	[0.330]	[1.840]	[0.300]	[0.893]	[0.075]	[0.825]	[0.121]
Export Status	-0.551	0.073	0.232	0.136	0.142	0.088	-1.419***	-0.019	-0.719	-0.093
	[0.558]	[0.124]	[0.859]	[0.116]	[0.620]	[0.120]	[0.492]	[0.029]	[0.470]	[0.070]
Wage^j_{06}	-0.168	-0.011	-0.224	-0.023	-0.275	0.003	-0.009	-0.007	-0.227*	-0.037**
	[0.206]	[0.033]	[0.172]	[0.025]	[0.193]	[0.033]	[0.125]	[0.005]	[0.112]	[0.016]
Capital	0.098**	0.009	-0.115*	-0.005	0.037	0.004	0.040	0.003	0.035	0.007*
	[0.041]	[0.008]	[0.065]	[0.009]	[0.049]	[0.008]	[0.032]	[0.002]	[0.029]	[0.004]
Hicks-neutral, φ	-0.326***	-0.024*	-0.100	0.011	-0.284***	-0.028**	0.010	0.002	-0.088**	-0.001
	[0.075]	[0.014]	[0.100]	[0.015]	[0.081]	[0.014]	[0.062]	[0.003]	[0.044]	[0.007]
Foreign-Owned	-0.240	-0.141*	-0.451	-0.115	-0.470	-0.143*	0.263	-0.016	-0.110	-0.010
	[0.305]	[0.078]	[0.470]	[0.079]	[0.372]	[0.077]	[0.262]	[0.020]	[0.204]	[0.030]
R&D	0.016	-0.021	-0.226	-0.038	-0.047	-0.034	0.321***	0.016	0.198	0.038**
	[0.174]	[0.040]	[0.272]	[0.040]	[0.214]	[0.040]	[0.116]	[0.011]	[0.122]	[0.018]
Training	0.133	0.013	-0.200	0.002	0.117	0.006	0.200**	0.012*	0.110	0.021*
	[0.119]	[0.025]	[0.166]	[0.025]	[0.130]	[0.025]	[0.093]	[0.006]	[0.083]	[0.012]
Wage^j_{96}	-0.374	-0.123***	0.114	0.020	-0.642***	-0.118***	0.314**	0.016***	0.139	0.036*
	[0.244]	[0.046]	[0.233]	[0.029]	[0.241]	[0.045]	[0.146]	[0.006]	[0.141]	[0.019]
$\ln(L_s/L_u)_{96}$	0.336***		0.090**		0.397***		0.297***			
	[0.030]		[0.042]		[0.036]		[0.045]			
d_u	0.193		0.106		-0.102		-0.237			
	[0.281]		[0.086]		[0.066]		[0.161]			
d_s	-0.903***		0.194		0.087		0.066			
	[0.099]		[0.163]		[0.093]		[0.078]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.371***		0.087**		0.416***		0.262***		
		[0.036]		[0.044]		[0.034]		[0.053]		
$\ln(L^n/L^p)_{96}$									0.378***	
									[0.025]	
d^p									-0.112**	
									[0.045]	
d^n									0.034	
									[0.040]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.365***
										[0.026]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.151	0.343	0.569	0.704	0.510	0.609	0.225	0.084	0.073	0.279
No. Obs	2,529	3,498	1,703	3,208	2,756	3,498	1,325	3,498	3,208	3,498

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.15: Robustness Check: Standards

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dependent Variable	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Standards	5.354*	1.365**	1.931*	0.828**	5.976*	1.220**	0.502	0.222**	1.053	-0.078
	[3.000]	[0.618]	[1.148]	[0.393]	[3.083]	[0.559]	[0.816]	[0.093]	[1.230]	[0.178]
Wage_{06}^j	0.319	0.105	-0.262	-0.028	0.481	0.118	-0.526***	-0.005	0.208	-0.006
	[0.446]	[0.084]	[0.186]	[0.035]	[0.439]	[0.076]	[0.157]	[0.009]	[0.173]	[0.023]
Capital	-0.051	-0.011	-0.060	-0.007	-0.075	-0.011	0.028	-0.000	0.003	0.008
	[0.108]	[0.018]	[0.045]	[0.013]	[0.104]	[0.016]	[0.031]	[0.003]	[0.037]	[0.006]
Hicks-neutral, φ	-0.414***	-0.050**	-0.109	-0.003	-0.317***	-0.053**	-0.040	-0.005	-0.139***	-0.003
	[0.125]	[0.026]	[0.085]	[0.019]	[0.118]	[0.023]	[0.070]	[0.005]	[0.052]	[0.008]
Foreign-Owned	-0.337	-0.091	0.350	-0.069	-0.490	-0.067	0.137	-0.022	-0.159	-0.012
	[0.672]	[0.132]	[0.392]	[0.085]	[0.729]	[0.115]	[0.217]	[0.022]	[0.205]	[0.030]
R&D	-0.752	-0.173	-0.268	-0.095	-0.502	-0.143	0.121	0.003	0.058	0.048
	[0.546]	[0.113]	[0.278]	[0.076]	[0.490]	[0.103]	[0.133]	[0.020]	[0.219]	[0.033]
Training	-0.176	-0.076	-0.128	-0.042	-0.271	-0.066	0.150	-0.004	-0.039	0.020
	[0.313]	[0.071]	[0.160]	[0.051]	[0.368]	[0.065]	[0.110]	[0.011]	[0.151]	[0.021]
Wage_{96}^j	-0.426	-0.083	0.441**	0.043	-0.432	-0.082	0.802***	0.024***	0.151	0.046**
	[0.359]	[0.067]	[0.217]	[0.036]	[0.356]	[0.060]	[0.198]	[0.008]	[0.140]	[0.018]
$\ln(L_s/L_u)_{96}$	0.307***		0.138***		0.416***		0.392***			
	[0.058]		[0.040]		[0.054]		[0.034]			
d_u	0.344		0.247***		0.187		-0.323			
	[0.423]		[0.091]		[0.164]		[0.225]			
d_s	-0.751***		0.151		0.292**		0.166			
	[0.178]		[0.137]		[0.146]		[0.121]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.309***		0.160***		0.385***		0.249***		
		[0.081]		[0.042]		[0.070]		[0.051]		
$\ln(L^n/L^p)_{96}$									0.412***	
									[0.023]	
d^p									-0.077	
									[0.049]	
d^n									0.111**	
									[0.052]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.389***
										[0.027]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.707	0.643	0.541	0.640	0.993	0.550	0.653	0.662	0.496	0.322
No. Obs	2,186	3,329	1,318	2,958	2,435	3,329	924	3,329	2,958	3,329

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.16: Robustness Check: Capital-Skill Complementarity

Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
Dependent Variable	$\ln(L_s^p/L_u^p)$	$\left(\frac{L_s^p}{L_s^p+L_u^p}\right)$	$\ln(L_s^n/L_u^n)$	$\left(\frac{L_s^n}{L_s^n+L_u^n}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L_s/L_u)$	$\left(\frac{L_s}{L_s+L_u}\right)$	$\ln(L^n/L^p)$	$\left(\frac{L^n}{L^n+L^p}\right)$
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	5.716***	1.476***	3.639*	0.525	7.500***	1.460***	3.113**	0.273**	2.609**	0.184
	[2.130]	[0.464]	[2.060]	[0.378]	[2.901]	[0.465]	[1.521]	[0.137]	[1.159]	[0.126]
Capital-Skill Comp.	0.388	0.081	-0.021	-0.017	0.513	0.114	-0.143	0.002	0.246	0.004
	[0.511]	[0.090]	[0.567]	[0.093]	[0.862]	[0.108]	[0.423]	[0.031]	[0.189]	[0.016]
Export	-0.141	-0.035	-0.498***	-0.077***	-0.166	-0.014	-0.559***	-0.043***	-0.124	-0.025*
	[0.315]	[0.062]	[0.143]	[0.024]	[0.504]	[0.073]	[0.137]	[0.009]	[0.130]	[0.015]
Wage^j_{06}	-0.176	-0.057	-0.097	-0.017	-0.216	-0.045	-0.088	-0.009	-0.056	-0.007
	[0.286]	[0.053]	[0.210]	[0.037]	[0.300]	[0.055]	[0.181]	[0.011]	[0.147]	[0.017]
Capital	-0.230	-0.054	-0.045	-0.003	-0.351	-0.081	0.081	-0.004	-0.185	-0.002
	[0.378]	[0.065]	[0.454]	[0.075]	[0.636]	[0.078]	[0.342]	[0.025]	[0.142]	[0.012]
Hicks-neutral, φ	-0.265***	-0.004	-0.038	0.014	-0.219*	-0.004	-0.060	-0.000	-0.093*	-0.007
	[0.098]	[0.022]	[0.090]	[0.016]	[0.120]	[0.024]	[0.089]	[0.005]	[0.052]	[0.006]
Foreign-Owned	-0.527	-0.139*	-0.288	-0.051	-0.607	-0.124	-0.373	-0.031	-0.376**	-0.030
	[0.366]	[0.076]	[0.291]	[0.057]	[0.419]	[0.076]	[0.248]	[0.020]	[0.188]	[0.022]
R&D	-0.161	-0.007	-0.047	-0.016	-0.005	0.008	-0.050	0.007	0.145	0.018
	[0.226]	[0.050]	[0.245]	[0.040]	[0.325]	[0.053]	[0.159]	[0.014]	[0.116]	[0.014]
Training	0.212	0.051	-0.082	-0.031	0.440	0.065	-0.039	0.003	0.103	0.008
	[0.231]	[0.051]	[0.224]	[0.038]	[0.468]	[0.061]	[0.160]	[0.012]	[0.100]	[0.011]
Wage^j_{96}	-0.993*	-0.214**	0.226	0.042	-1.255*	-0.236**	0.214	0.021	-0.260	0.002
	[0.515]	[0.092]	[0.223]	[0.038]	[0.746]	[0.102]	[0.202]	[0.013]	[0.212]	[0.022]
$\ln(L_s/L_u)_{96}$	0.379***		0.134*		0.485***		0.298***			
	[0.078]		[0.071]		[0.165]		[0.047]			
d_u	-0.267		0.169**		-0.138		-0.358			
	[0.402]		[0.075]		[0.158]		[0.229]			
d_s	-1.098***		0.309*		-0.209		0.176			
	[0.329]		[0.172]		[0.359]		[0.163]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.418***		0.114*		0.516***		0.218**		
		[0.329]		[0.068]		[0.137]		[0.087]		
$\ln(L^n/L^p)_{96}$									0.413***	
									[0.032]	
d^p									-0.233**	
									[0.119]	
d^n									0.060	
									[0.046]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.380***
										[0.029]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.101	0.291	0.636	0.763	0.021	0.164	0.954	0.834	0.022	0.070
No. Obs	2,542	3,244	1,795	2,036	3,012	3,244	1,487	2,082	3,115	3,244

Notes: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.17: Importing and Standardized Production

Dep. Var.	Standards									
Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	1.491*	1.425*	1.819*	1.622*	2.268	1.395*	1.113	1.851*	1.467*	1.517*
	[0.877]	[0.851]	[1.002]	[0.966]	[2.112]	[0.843]	[1.282]	[1.055]	[0.850]	[0.826]
Wage^j_{06}	-0.114**	-0.114**	-0.060	-0.039	-0.136	-0.114***	-0.059	-0.060	-0.117**	-0.114**
	[0.045]	[0.045]	[0.039]	[0.040]	[0.098]	[0.044]	[0.099]	[0.039]	[0.052]	[0.046]
capital	0.014	0.014	0.007	0.013	0.005	0.014	0.012	0.011	0.011	0.014
	[0.010]	[0.009]	[0.011]	[0.012]	[0.025]	[0.009]	[0.020]	[0.012]	[0.011]	[0.010]
Hicks-neutral, φ	0.008	0.010	0.002	0.006	-0.000	0.010	0.033	0.005	0.006	0.009
	[0.020]	[0.020]	[0.023]	[0.024]	[0.034]	[0.019]	[0.038]	[0.023]	[0.022]	[0.020]
Foreign-Owned	0.052	0.046	0.031	0.043	0.066	0.048	0.030	0.039	0.052	0.046
	[0.104]	[0.102]	[0.118]	[0.111]	[0.119]	[0.101]	[0.105]	[0.117]	[0.104]	[0.105]
R&D	0.121**	0.122**	0.102	0.117*	0.072	0.122**	0.078	0.115*	0.117*	0.119**
	[0.059]	[0.057]	[0.065]	[0.063]	[0.089]	[0.057]	[0.061]	[0.066]	[0.060]	[0.060]
Training	0.077***	0.078***	0.063*	0.084**	0.076	0.079***	0.088**	0.072**	0.080***	0.077***
	[0.029]	[0.028]	[0.034]	[0.033]	[0.047]	[0.028]	[0.044]	[0.034]	[0.031]	[0.030]
Wage^j_{96}	-0.032	-0.029	-0.006	0.007	-0.074	-0.029	-0.049	-0.007	-0.005	-0.032
	[0.059]	[0.058]	[0.043]	[0.046]	[0.091]	[0.057]	[0.086]	[0.043]	[0.064]	[0.059]
$\ln(L_s/L_u)_{96}$	0.007		-0.018		0.005		-0.024			
	[0.009]		[0.012]		[0.012]		[0.021]			
d_u	-0.132				-0.024		0.070			
	[0.107]				[0.024]		[0.104]			
d_s	-0.033		-0.038		-0.003		-0.072			
	[0.023]		[0.044]		[0.031]		[0.047]			
$\left(\frac{L_s}{L_s+L_u}\right)_{96}$		0.042		0.009		0.051		-0.088		
		[0.055]		[0.046]		[0.049]		[0.270]		
$\ln(L^n/L^p)_{96}$									0.001	
									[0.008]	
d^p									-0.028*	
									[0.017]	
d^n									-0.040**	
									[0.018]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										0.072
										[0.051]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.460	0.428	0.399	0.379	0.647	0.421	0.202	0.411	0.472	0.426
No. Obs	3,329	3,329	3,329	2,958	2,720	3,329	1,194	3,329	2,958	3,329

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. The education threshold used to determine a skilled production worker is a highschool diploma, while the threshold used for a skilled non-production worker is a college degree. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.

Table G.18: Exporting, Initial Skill-Levels, and SBTC

Dep. Var.	Export Status									
Occupation	Production		Non-Production		All		All		All	
Threshold	Highschool		College		Highschool		College		Occupation	
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Import Status	-0.579	-0.580	-0.739	-0.553	-0.532	-0.584	-0.264	-0.681	-0.342	-0.530
	[0.413]	[0.408]	[0.478]	[0.432]	[0.544]	[0.412]	[0.450]	[0.462]	[0.359]	[0.386]
Wage^j_{06}	0.035	0.035	-0.025	-0.028	0.061	0.035	-0.005	-0.026	0.038	0.035
	[0.031]	[0.031]	[0.025]	[0.026]	[0.045]	[0.031]	[0.047]	[0.025]	[0.032]	[0.031]
Capital	0.033***	0.033***	0.035***	0.036***	0.037***	0.033***	0.033***	0.036***	0.032***	0.035***
	[0.007]	[0.007]	[0.008]	[0.008]	[0.010]	[0.007]	[0.012]	[0.008]	[0.007]	[0.007]
Hicks-neutral, φ	0.029**	0.029**	0.030**	0.034**	0.034**	0.029**	0.004	0.032**	0.030**	0.030**
	[0.012]	[0.012]	[0.013]	[0.013]	[0.014]	[0.012]	[0.017]	[0.013]	[0.012]	[0.012]
Foreign-Owned	0.246***	0.246***	0.260***	0.237***	0.244***	0.248***	0.201**	0.259***	0.220***	0.245***
	[0.086]	[0.087]	[0.096]	[0.087]	[0.092]	[0.087]	[0.092]	[0.093]	[0.077]	[0.085]
R&D	0.112***	0.112***	0.118***	0.114***	0.115**	0.114***	0.084**	0.121***	0.106***	0.118***
	[0.042]	[0.041]	[0.046]	[0.043]	[0.045]	[0.042]	[0.042]	[0.044]	[0.039]	[0.041]
Training	0.082***	0.082***	0.086***	0.085***	0.079***	0.084***	0.087***	0.090***	0.078***	0.087***
	[0.020]	[0.019]	[0.023]	[0.021]	[0.022]	[0.020]	[0.027]	[0.022]	[0.019]	[0.020]
Wage^j_{96}	0.064	0.064	0.016	0.025	0.077*	0.063	0.004	0.015	0.073*	0.060
	[0.040]	[0.040]	[0.028]	[0.030]	[0.046]	[0.040]	[0.053]	[0.028]	[0.039]	[0.039]
$\ln(L^p_s/L^p_u)_{96}$	0.009		-0.001		0.004		-0.029**			
	[0.006]		[0.012]		[0.006]		[0.012]			
d^p_u	0.040		0.018		-0.012		0.033			
	[0.065]		[0.016]		[0.011]		[0.054]			
d^p_s	-0.033**		-0.043*		-0.012		-0.049*			
	[0.014]		[0.023]		[0.014]		[0.028]			
$\left(\frac{L^p_s}{L^p_s+L^p_u}\right)_{96}$		0.067**		0.065*		0.053*		0.025		
		[0.033]		[0.035]		[0.031]		[0.107]		
$\ln(L^n/L^p)_{96}$									-0.013**	
									[0.005]	
d^p									-0.017*	
									[0.010]	
d^n									-0.025**	
									[0.011]	
$\left(\frac{L^n}{L^n+L^p}\right)_{96}$										-0.074**
										[0.036]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value	0.199	0.195	0.358	0.289	0.273	0.192	0.356	0.323	0.118	0.170
No. Obs	3,619	3,619	3,619	3,226	2,994	3,619	1,395	3,619	3,226	3,619

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors are in square brackets. The sample of initial non-importers is used in all regressions. The education threshold used to determine a skilled production worker is a highschool diploma, while the threshold used for a skilled non-production worker is a college degree. Import status is treated as an endogenous variable in all columns. It is instrumented with both the distance to port and the share of imports shipped by air.