The Differential Effects of Exporting on Input Productivities

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January, 2023

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Abstract

Many empirical studies document that entering the export market raises a firm's productivity. I study whether entering the export market results in differential increases in input productivities at the firm-level (non-neutral change). I develop a model that separately identifies firm-level skilled and unskilled labor-augmenting productivities, and material input prices. Applying the model to data on the Colombian apparel manufacturers, I find that exporting raises the skilled labor-augmenting productivity 7.2-percentage point more than the unskilled counterpart. A counterfactual simulation in which exporting raises the two productivities equally, the mean-differences in skilled-to-unskilled employee ratios between exporters and non-exporters are 50 percent smaller than the data counterparts. The result suggests that non-neutral productivity gain from trade is central in shaping the input allocation differences between exporters and non-exporters.

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I Introduction

Many empirical studies document that exporting raises the firm/plant's future productivity-which is oftentimes labeled 'learning-by-exporting'.[1] Firms who enter the export market can improve their productivity through technical support from trading partners, adopting a newly innovated technology abroad, or upgrading product quality. Previous studies confirm the productivity effect of exporting by documenting that exporting raises the firm's total factor productivity (TFP). However, the papers do not consider the possibility that the mechanisms whereby exporting raises the firm-level productivity could enhance the firm's productivities in a biased way: a particular factor-augmenting productivity increases more than others in response to the past export experience. The goals of this paper are to (i) provide micro evidence on biased productivity gains from exporting in the context of skilled and unskilled labor-augmenting productivities and (ii) quantify the contribution of biased gains to the differences in skill intensity (skilled-to-unskilled ratios) between exporters and non-exporters.

Exploring the bias in productivity gains from the exposure to export is important to understand how the exposure shapes the differences in input allocation between exporters and non-exporters. Suppose exporting raises a particular input-augmenting productivity more than others. All else equal, exporters and non-exporters differ in the relative productivity. Due to the different relative productivity, exporters would have a higher marginal product of the input whose productivity increases more from exporting. Thus, exporters demand that input more (less) than do non-exporters when inputs are gross substitutes (complements). In this way, exporters and non-exporters make a different input allocation decision. In this way, exploring whether productivity gains from exporting are biased has a direct implication to input allocation differentials between exporters and non-exporters.

My motivation for focus on skilled and unskilled labor-augmenting productivities improvements from exporting comes from the two stylized facts in the Colombian apparel industry. First, plant-level skilled-to-unskilled ratios largely deviate from predicted ratios by a model with neutral productivity alone. Such large deviations suggest the existence of skilled and unskilled labor-augmenting productivities within a simple framework with

[1] See Tybout (2003) and Greenaway and Kneller (2007) for the review of literature on the positive productivity effect of exporting at the firm level.

CES production function. Second, I further document that large deviations are strongly connected to export status in the previous period even after controlling for plant-level fixed effects and the possible persistence of the deviations. The result suggests evidence that exporting raises a particular productivity more than the other- biased productivity gains from exporting.

This paper measures the effects of exporting on skilled and unskilled labor-augmenting productivities as well as the elasticity of substitutions between skilled and unskilled workers. I document that skilled labor-augmenting productivity increases more than an unskilled one. The estimated elasticity of substitutions between skilled and unskilled workers is 2.6, which indicates skilled and unskilled workers are gross-substitutes, which echoes the findings in labor economics literature (Acemoglu and Autor (2011)). Thus, all else equal, exporters become more skill-intensive than non-exporters. I further show that biased gains from exporting are quantitatively important in shaping the differences in skill intensity between exporters and non-exporters in the Colombian apparel industry.

I recover skilled and unskilled labor-augmenting productivities using data on skilled and unskilled wage rates and the number of skilled and unskilled workers. Observing expenditures and quantities for skilled and unskilled workers separately establishes the identifiability of skilled and unskilled labor-augmenting productivities. The optimality conditions of the plant's optimization problem show that skilled-to-unskilled expenditure ratios depend on skilled-to-unskilled worker ratios and relative productivity. Since I can observe the expenditure ratios and the worker ratios, I recover the relative skilled (or unskilled) productivity through the optimality conditions of the plant's optimization problem. I recover the remaining labor-augmenting productivity by inverting the first-order condition,[2] and then retrieve all the labor-augmenting productivities.

Since the bias of productivity gains from exporting toward a particular factor hinges on whether inputs of interest are substitutes or complements, the precise estimate of the substitution patterns between skilled and unskilled workers is crucial. Yet, the failure to control for input prices leads to a downwardly biased estimates of the elasticity of

[2] This strategy is different from Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) who use proxy variables such as investment or material expenditures to control for unobserved productivity. To follow, I need enough observations reporting positive investment. However, in the Colombian apparel industry, about 40 percent of observations report zero or negative investment. Thus, investment policy function would not be invertible. Given this data feature, I exploit the parametric inversion of first-order conditions in the spirit of Doraszelski and Jaumandreu (2013).

substitutions between inputs (Grieco, Li, and Zhang (2016)), which generate incorrect conclusion on the substitution patterns. Since the input prices are not observable in the data, I address this concern by leveraging the parametric inversion of the first-order conditions in the spirit of Grieco et al. (2016) and Grieco et al. (2022).

To quantify the relevance of skilled-biased productivity gains from exporting (skilled-biased learning-by-exporting), I simulate a counterfactual scenario in which skilled and unskilled-labor augmenting productivities increase equally in response to the past export status. By comparing the differences in skill intensity between exporters and non-exporters in real and counterfactual worlds, I find that the skilled-biased productivity gains explain 50 percent to 80 percent of the observed differences between exporters and non-exporters. In addition, I find that the skilled-biased productivity gains have a long-run impact on the differences in skill intensity between exporters and non-exporters due to the high persistence of skilled-labor augmenting productivity.

This paper contributes to the strand of literature studying the link between firm-level export and the firm's future performance. Specifically, I extend this strand by providing micro evidence that productivity gains from exporting could be biased. Several recent empirical studies report the positive effect of exporting on firm-level productivity. [3] However, all these studies look at the relationship between past exporting experience and total factor productivity (TFP) and thus do not deliver the implication to the relationship between export status and future input allocations. I contribute to the literature by documenting that export status alters future input allocations via a skilled-biased learning-by-exporting channel.

This paper is related to the recent two studies on the relationship between firm-level trade status and factor-augmenting productivities. Balat, Brambilla, and Sasaki (2016) show that exporters in Chile are more skilled labor efficient than non-exporters. Imbruno and Ketterer (2018) show manufacturing plants in Indonesia become more energy-efficient when they start importing foreign material goods within a reduced-form framework. My empirical results complement Balat et al. (2016) by further exploring the quantitative implication of the biased gains from exporting to the skill intensity differences between exporters and non-exporters. Besides, my work complements Imbruno

[3] Examples are as follows: Aw et al. (2000) for Korean and Taiwanese manufacturers, Van Biesebroeck (2005) for African manufacturers, De Loecker (2007), De Loecker (2013) for Slovenian manufacturers, Aw et al. (2011) for Taiwanese electronic manufacturers, and Bai et al. (2017) for Chinese manufacturers

and Ketterer (2018) by structurally recovering factor-augmenting productivities and then measuring the responses of them to export status in the previous period.

This paper also joins the strand of literature that estimates factor-augmenting productivities. Though many studies in the productivity literature focus on measuring neutral productivity due to the scarcity of data, recent studies such as Doraszelski and Jaumandreu (2018), Zhang (2019), and Raval (2019) estimate factor-augmenting productivities by using the first-order conditions of the firm optimization problem. However, the methodology requires researchers to observe firm-level material prices to tease out labor-augmenting productivity from other factor-augmenting productivities. However, a widely used manufacturing survey typically do not record firm-level material prices and quantities separately. [4] My work thus complements these studies by augmenting the spirit of Grieco et al. (2016), so that a researcher can control for unobserved material prices and recover a particular factor-augmenting productivity such as skilled (or unskilled) labor-augmenting or energy-augmenting productivity.

The paper is organized as follows. Section II describes the data and presents the motivating facts. Section III lays out the model providing the first-order conditions used for identifying non-Hicks-neutral productivity. Section IV describes the estimation strategy. Section V presents and discusses the empirical results. Section VI conducts the counterfactual exercise to quantify the role of non-Hicks-neutral productivity gains from exporting in explaining the skilled labor demand of exporters. Section VII concludes the paper.

II Data and Suggestive Evidence

II.I Data

I employ the Colombian manufacturing survey from the Departamento Administrativo Nacional de Estadistica (DANE), which spans from 1981 to 1991. This panel dataset allows me to track each manufacturing plant's detailed information about domestic and export sales, material expenditures, the number of workers, employee payments (salaries

[4] For instance, widely used manufacturing datasets such as Chilean, Chinese, Colombian, and Slovenian manufacturing survey data record firm-level revenues and material expenditures. Few datasets such as Spanish or Indian manufacturing dataset record output prices and materials prices.

+ benefits), investment, and capital stock. For a more detailed discussion of the data, refer to Roberts (1996).

The notable feature of the survey is that the surveyed plants report the number of workers and the corresponding payments by type of workers. This information allows me to measure the plant-level average wage rates for skilled workers and unskilled workers, which are crucial for the identification of skilled and unskilled labor-augmenting productivities. I measure the number of skilled workers as the sum of variables labeled as “management”, “technicians”, and “skilled workers”. Similarly, I measure the number of unskilled workers as variables labeled as “unskilled workers”. I measure the total payments to skilled and unskilled workers as the sum of the corresponding payments to each category. The wage rates for skilled workers are computed by the ratio of the total payments to the number of workers. The wage rates for unskilled workers are measured by the same manner.

I particularly focus on the plants in the apparel industry who operated at least two years consecutively. The choice of the industry reflects several considerations. First, in the apparel industry, logged skilled-to-unskilled ratios and logged capital stock are weakly correlated (0.08). This features capital-skill complementarity channel would not be enough to explain the relative skilled labor demand of the plants in this industry. Thus, I can focus on the role of skilled and unskilled labor-augmenting productivities in explaining the relative skilled labor demand. Second, during the sample period, when a plant participates in trade activities, it usually does exporting only. Hence, I can rule out the possibility that increases in productivities due to exporting are driven by the spurious correlation with productivities gains from importing.

To simplify empirical analysis, I restrict the sample to plants who always hired both skilled and unskilled workers during the sample period. That is, I assume away any non-convex costs associated with labor choices, and treat skilled and unskilled workers as flexibly adjusted inputs. By doing so, I can resort to first order conditions with respect to skilled and unskilled workers to recover skilled and unskilled labor-augmenting productivities. This simplification is a reasonable starting point because of two reasons. First, of the sample observations, about nine percent of total reports either zero skilled workers or zero unskilled workers. Second, most exports in the Colombian apparel industry were driven by plants who hire skilled workers during the sample period. I clean the data following the way described by Roberts (1996). The cleaning process leaves 7,620 plant-year observations in the apparel industry.

II.II Facts

This section describes motivating reduced form evidence. In Section II.II.1, I document that the observed skilled-to-unskilled ratios in the data largely deviate from the skilled-to-unskilled ratios predicted by the model without skilled and unskilled labor-augmenting productivities. If a production function of plants is described by only neutral productivity, variations in relative wage rates for skilled workers can explain most of variations in skilled-to-unskilled ratios. Therefore, if the deviations are significantly large, it suggests the existence of skilled and unskilled labor-augmenting productivities. In Section II.II.2, I show that those deviations are tightly linked to plants' export status in the previous period. In simple CES framework, the deviations are proxy for relative productivity of unskilled workers scaled up by the elasticity of substitution. If exporting raises a particular productivity higher than the other, the deviations are more likely to be explained by plants' export status in the previous period.

II.II.1 Evidence of Factor-augmenting Productivities

To illustrate the intuition for why deviations from prediction by first order conditions are evidence for skilled and unskilled labor productivities, I consider a widely accepted CES production function. Assume that skilled and unskilled workers are flexibly chosen by plants, skilled-to-unskilled ratios and the relative wage rates are in the following simple log-linear relationship.

$$\ln \frac{L_{jt}^S}{L_{jt}^U} = -\sigma \ln \frac{W_{jt}^S}{W_{jt}^U} + (1-\sigma)(a_{jt}^U - a_{jt}^S). \tag{1}$$

Here, σ is the elasticity of substitution between skilled and unskilled workers. L_{jt}^S and L_{jt}^U are the number of skilled and unskilled workers, respectively. W_{jt}^S and W_{jt}^U are the corresponding wage rates. Finally a_{jt}^S, a_{jt}^U are skilled and unskilled labor-augmenting productivities, respectively. If plant-level productivity is neutral, the last term in equation (1) will be omitted and thus the skilled-to-unskilled ratios are entirely explained by variations in relative wage rates. Thus, if I observe that the relative wage rates can explain only a small portion of skilled-to-unskilled ratios, I could use that result as evidence of skilled and unskilled labor-augmenting productivities.

Table 1 displays a series of regression of logged skilled-to-unskilled ratios on logged relative wage rates. I also employ year dummies, ownership dummies, location dummies, logged capital, and its squared as control covariates. I include the logged capital to rule out the possibility that capital-skill complementarity plays a dominant role in explaining the skilled labor demand in the Colombian apparel industry. Regression results suggest strong evidence of skilled and unskilled labor-augmenting productivities. From the sixth column of Table 1, we see that logged relative wage rates and all the covariates can only explain at most 8.4% of the variations in skilled-to-unskilled ratios.

Figure 1 further provides evidence of skilled and unskilled labor-augmenting productivities. In Figure 1, I plot the skilled-to-unskilled ratios predicted by first order conditions and the data counterpart with the value of the year 1981 normalized to be one. Following Zhang (2019), I compute predicted skilled-to-unskilled ratios by using relative wage variations and the estimates of the elasticity of substitutions reported in Table 1. Note that while skilled-to-unskilled ratios increase by around 70%, the simulated ratios increase by only 20% during the sample period. This picture thus reinforces the argument that relative wage rates are insufficient to explain skilled-to-unskilled ratios, and indicate the evidence of skilled and unskilled labor-augmenting productivities.

II.II.2 Evidence of Biased Productivity Gains from Exporting

Let $\hat{\xi}_{jt}$ be the residuals from the regression in sixth column of Table 1. The residuals are capturing the deviations of skilled-to-unskilled ratios from the prediction by the model with only neutral productivity. Then by equation (1), the residuals $\hat{\xi}_{jt}$ are proxy for $(1-\sigma)(a^U_{jt} - a^S_{jt})$. Thus, I can draw suggestive evidence of biased productivity gains from exporting by regressing $\hat{\xi}_{jt}$ on lagged indicator of exporting. If exporting raises both productivities equally, the improvement of a^S_{jt} due to exporting would cancel out the improvement of a^U_{jt} due to exporting. In this case, we would not see the significant link between the residuals and lagged indicator of exporting.

However, regressing $\hat{\xi}_{jt}$ on lagged indicator of exporting through OLS would be clouded by endogeneity of exporting decision: It is probable that plants whose productivities are combined in a way of generating higher skilled-to-unskilled ratios (higher $\hat{\xi}_{jt}$) would more likely to enter the foreign market. In this case, OLS would be upwardly biased. To bypass the endogeneity issue, I employ a dynamic panel approach which controls for plant-level unobserved fixed effects and a lagged dependent variable (Arellano and Bond (1991) and Blundell and Bond (1998)).

Table 2 provides evidence for biased productivity gains from exporting. In Table 2, I report the estimation results from OLS, Arellano and Bond (1991), and Blundell and Bond (1998). I find that even after controlling for unobserved plant-level fixed effects and $\hat{\xi}_{j,t-1}$, exporting is associated with the residuals which are proxy for $(1-\sigma)(a^U_{jt}-a^S_{jt})$. The estimates of the coefficient to lagged indicator of exporting drawn from Arellano and Bond (1991), and Blundell and Bond (1998) are statistically significant at 10% and 5% significance levels, respectively. Furthermore, exporting is positively correlated with $\hat{\xi}_{jt}$. These results indicate that it is more likely that productivity gains from exporting is non-neutral and favor skilled over unskilled workers.

Figure 2 also suggests evidence of biased productivity gains from exporting. Note that, as Table 2 indicates, exporters would gain skill-biased productivity and thus their skilled-to-unskilled ratios become more deviated from the predicted ratios by the model without non-neutral productivities. Figure 2 confirms this conjecture. In Figure 2, I display the time evolution of the deviations obtained in Figure 1 for exporters and non-exporters. While the deviations of exporters have increased by five to nine times during the sample period, the non-exporters' counterpart have increased pretty moderately.

Although the results in Table 2 and Figure 2 indicate that exporting raises productivities biased toward skilled workers, I cannot answer the question which labor-augmenting productivity improves more than the other. To answer this question, I need to estimate the elasticity of substitutions between skilled and unskilled workers, and this motivates the structural model discussed in the next section.

III Model

In this section, I model plants' production and input choice decisions. Specifically, I embed factor-augmenting productivities (Doraszelski and Jaumandreu (2018)) to the model of firms that can serve multiple markets (Grieco et al. (2022)). In Section III.I, I lay out the model ingredients including demand and production functions, and transition process of skilled and unskilled labor-augmenting productivities. Section III.II describes plants' optimization problem. The optimality conditions from the optimization problem will be employed to identify skilled and unskilled labor-augmenting productivities along with the elasticity of substitution between skilled and unskilled workers.

III.I Model Ingredients

III.I.1 Demand and Production

At the beginning of period t, plant j faces constant elastic inverse demand curves in domestic (D) and export (X) markets, which are assumed to be monopolistically competitive: $P_{jt}^m = \kappa_m \Phi_t^m (Q_{jt}^m)^{1/\eta_m}$, where $m = D, X$. Here, Q_{jt}^m is the quantity demanded in market m and P_{jt}^m is the price firm j set in market m at time t. I allow for different demand elasticities to capture the possibility that plants have different market power in the domestic (η_D) and export markets (η_X). Φ_t^m is an aggregate time-variant demand shifter in market m. Finally κ_m captures time-invariant size of market m. I normalize size of the domestic market to one and let $\kappa = \kappa_X$. Thus, κ essentially captures the time-invariant size difference between the domestic and export markets.

Plant j produces output $Q_{jt} = Q_{jt}^D + e_{jt} Q_{jt}^X$ through the following CES function nesting a CES aggregation of skilled and unskilled workers with factor-augmenting productivities.

$$
\begin{aligned}
Q_{jt} &= [\alpha_L \tilde{L}_{jt}^{\gamma} + \alpha_M (\exp(a_{jt}^M) M_{jt})^{\gamma} + \alpha_K (\exp(a_{jt}^K) K_{jt})^{\gamma}]^{\frac{1}{\gamma}}, \\
\tilde{L}_{jt} &= [(\exp(a_{jt}^U) L_{jt}^U)^{\rho} + (\exp(a_{jt}^S) L_{jt}^S)^{\rho}]^{\frac{1}{\rho}},
\end{aligned}
$$

where M_{jt} and K_{jt} are material and capital, respectively, and $\tilde{L}_{jt}$ is a composite basket of unskilled worker L_{jt}^U and skilled workers L_{jt}^S. The elasticity of substitutions among labor, material, and capital is governed by γ, and the elasticity of substitutions between skilled and unskilled workers is governed by ρ. α_L, α_M, and α_K are the distribution parameters for labor, material, and capital. a_{jt}^f is a factor f-augmenting productivity, where $f = S, U, L, K$.

I cannot identify all the four factor-augmenting productivities together because the

Colombian manufacturing survey does not record plant-level output and material prices which can be other independent variations to identify material- and capital-augmenting productivities. Thus, in practice, for the sake of identification, I assume that skilled labor-, material- and capital-augmenting productivities are the same: $a^S_{jt} = a^M_{jt} = a^K_{jt}$. Then, the production function that I estimate is

$$Q_{jt} = \exp(a^S_{jt})[\alpha_L L^{\gamma}_{jt} + \alpha_M M^{\gamma}_{jt} + \alpha_K K^{\gamma}_{jt}]^{\frac{1}{\gamma}}, \tag{2}$$

$$\tilde{L}_{jt} = [(\exp(\tilde{a}^U_{jt})L^U_{jt})^{\rho} + (L^S_{jt})^{\rho}]^{\frac{1}{\rho}}, \tag{3}$$

where $\tilde{a}^U_{jt} = a^U_{jt} - a^S_{jt}$ is relative unskilled labor-augmenting productivity.

III.I.2 Transition Process

I model the transition process of skilled and unskilled labor-augmenting productivities as well as logged material prices p^m_{jt} as the following controlled Markov process:

$$\begin{bmatrix} a^S_{jt} \\ a^U_{jt} \\ p^m_{jt} \end{bmatrix} = g\left(\begin{bmatrix} a^S_{j,t-1} \\ a^U_{j,t-1} \\ p^m_{j,t-1} \end{bmatrix} \right) + \begin{bmatrix} g^s_e \\ g^u_e \\ g^m_e \end{bmatrix} e_{j,t-1} + \begin{bmatrix} \varepsilon^s_{jt} \\ \varepsilon^u_{jt} \\ \varepsilon^m_{jt} \end{bmatrix}, \tag{4}$$

where $e_{j,t-1}$ is an indicator whether or not the firm j was an exporter at time $t-1$, ε^s_{jt}, ε^u_{jt}, and ε^m_{jt} are unexpected productivity shocks which are $i.i.d.$ across firms and over time. The specification incorporates empirical findings that exporting raises plant's future productivity (Van Biesebroeck (2005), De Loecker (2007), Aw et al. (2011), De Loecker (2013)). These productivity gains could be due to technical support from a trading partner, technology adoption, or access to knowledge on product innovation, quality upgrading, or the preference of foreign consumers. The productivity changes induced by these activities can improve a particular factor-augmenting productivity more than the others. This biased change is captured by the differences between g^s_e and g^u_e. Allowing material prices to have impact on the other productivities is motivated by empirical findings of Kugler and Verhoogen (2012) that material input quality complements plant/firm-level productivity. Here, based on the empirical findings that more qualified materials are more expensive , I use the recovered material prices as measure of material input quality.

III.II Plant Optimization

At the beginning of period t, plants take their productivities (a^S_{jt}, a^U_{jt}), capital K_{jt}, export status e_{jt}, wages and material prices $(W^S_{jt}, W^U_{jt}, P^M_{jt})$, and aggregate demand shifters (Φ^D_t, Φ^X_t) as their state variables. Plants then optimally choose $(L^S_{jt}, L^U_{jt}, M_{jt})$, allocate (Q^D_{jt}, Q^X_{jt}), and decide whether or not to export in the next period $(e_{j,t+1})$ to maximize their expected discounted sum of future operating profits. Let Σ_{jt} be a state vector of the firm j at the beginning of the period t and $V(.)$ denote the value function. The corresponding Bellman equation is

$$\begin{aligned} V(\Sigma_{jt}) = \max_{L^U_{jt}, L^S_{jt}, M_{jt}, Q^D_{jt}, Q^X_{jt}, e_{j,t+1}} & \{P^D_{jt}Q^D_{jt} + e_{jt}P^X_{jt}Q^X_{jt} - W^U_{jt}L^U_{jt} - W^S_{jt}L^S_{jt} - P^M_{jt}M_{jt} \\ & - C(e_{jt}, e_{j,t+1}) + \beta E(V(\Sigma_{j,t+1})|\Sigma_{jt}, e_{j,t+1})\}, \\ & \text{subject to (2), (3), (4)}, Q^D_{jt} + e_{jt}Q^X_{jt} = Q_{jt}, \\ & \text{and } P^D_{jt} = \Phi^D_t (Q^D_{jt})^{1/\eta_D}, P^X_{jt} = \kappa \Phi^X_t (Q^X_{jt})^{1/\eta_X} \end{aligned} \tag{5}$$

where $C(.,.)$ is the non-convex export cost. The problem provides the optimality conditions concerning inputs $(L^S_{jt}, L^U_{jt}, M_{jt})$. These conditions are employed to identify skilled and unskilled labor-augmenting productivities while controlling for unobserved material prices.

IV Estimation

Following Grieco et al. (2022), I estimate the model through two-stage approach. In the first stage, I estimate the demand and production function parameters and recover skilled and unskilled labor-augmenting productivities. I then estimate the transition process parameters and document which productivity increases more in response to export status in the previous period.

IV.I Stage 1. Demand and Production Parameters

In this section, I recover the demand elasticities in both markets (η_D, η_X), the export market size κ, aggregate market demand shifters (Φ^D_t, Φ^X_t), and the production function parameters $(\gamma, \rho, \alpha_L, \alpha_M, \alpha_K)$ using the data on plant-level revenues, input and input expenditure. Throughout this section, I assume that econometricians observe both domestic and export revenues (R^D_{jt}, R^X_{jt}) with measurement errors (u^D_{jt}, u^X_{jt}) and these measurement errors are unobserved to plants when they make decisions.

$$R^D_{jt} = \Phi^D_t (Q^D_{jt})^{\frac{\eta_D+1}{\eta_D}} \exp(u^D_{jt}) \tag{6}$$
$$R^X_{jt} = \kappa \Phi^X_t (Q^X_{jt})^{\frac{\eta_X+1}{\eta_X}} \exp(u^X_{jt}) \tag{7}$$

The main challenge of estimating the production function parameters is that I need control for three latent plant-year specific variables: skilled and unskilled labor-augmenting productivities, and material prices. Following Doraszelski and Jaumandreu (2013), Doraszelski and Jaumandreu (2018) and Grieco et al. (2016), I parametrically invert the first-order conditions of the short-run profit maximization problem in order to control for the unobservables. More detailed derivation appears in Appendix A.

I first recover the closed form equation mapping the observables to relative unskilled labor productivity $\tilde{a}^U_{jt}$. By taking the ratios of the first-order conditions with respect to skilled labor and unskilled labor, I arrive at

$$\tilde{a}^U_{jt} = \frac{1}{\rho} \ln \frac{E^U_{jt}}{E^S_{jt}} + \ln \frac{L^S_{jt}}{L^U_{jt}}, \tag{8}$$

where E^U_{jt} is $W^U_{jt} L^U_{jt}$ and $E^S_{jt} = W^S_{jt} L^S_{jt}$. Besides, by substituting this term back into (3), I represent L_{jt} as a closed form function of observed variables.

$$L_{jt} = (\frac{E^L_{jt}}{E^S_{jt}})^{\frac{1}{\rho}} L^S_{jt}, \tag{9}$$

where $E^L_{jt} = E^S_{jt} + E^U_{jt}$.

Using the first-order conditions concerning skilled labor and material, M_{jt} is also linear in L^S_{jt}.

$$M_{jt} = (\frac{\alpha_L}{\alpha_M} \frac{E^M_{jt}}{E^L_{jt}})^{\frac{1}{\gamma}} (\frac{E^L_{jt}}{E^S_{jt}})^{\frac{1}{\rho}} L^S_{jt}, \tag{10}$$

where $E^M_{jt} = P^M_{jt} M_{jt}$. Therefore, upon recovering the production function parameters, I retrieve the material inputs employed by plant j in period t.

Substituting (9) and (10) back into the domestic revenue equation, I arrive at the following estimating equation.

$$\ln R_{jt}^{D} = \ln \frac{\eta_D}{\eta_D + 1} + \ln[E_{jt}^{M} + E_{jt}^{L}(1 + \frac{\alpha_K}{\alpha_L}(\frac{K_{jt}}{L_{jt}^{S}})^{\gamma}(\frac{E_{jt}^{S}}{E_{jt}^{L}})^{\frac{\gamma}{\rho}})] + u_{jt}^{D}, \tag{11}$$

where u_{jt}^{D} is measurement errors to domestic revenues. To identify all the parameters, I need to impose restrictions on the distribution parameters. Equation (10), in conjunction with the normalization restriction that the geometric mean of inputs is one, provides a restriction for identification of α_M.

$$\frac{\alpha_M}{\alpha_L} = \frac{\bar{E}^{M}}{\bar{E}^{L}}(\frac{\bar{E}^{L}}{\bar{E}^{S}})^{\frac{\gamma}{\rho}},$$

where $\bar{E}$ refers to the geometric mean of expenditures. To identify α_K, I follow Grieco et al. (2016) and Grieco et al. (2022) and restrict the sum of distribution parameters to be one.

$$\alpha_L + \alpha_M + \alpha_K = 1$$

I estimate equation (11) through nonlinear least squared (NLLS) subject to the two additional restrictions using the observations serving the domestic market only.

The remaining parameters to be estimated are $(\eta_X, \kappa, \Phi_t^{D}, \Phi_t^{X})$. Using from the first-order conditions concerning Q_{jt}^{D} and Q_{jt}^{X}, I derive the following linear relation between R_{jt}^{D} and R_{jt}^{X}

$$\ln R_{jt}^{X} = -\eta_X \ln \kappa + (\eta_X + 1)\ln(\frac{\eta_X}{\eta_D}\frac{\eta_D + 1}{\eta_X + 1}) + \frac{\eta_X + 1}{\eta_D + 1}\ln R_{jt}^{D} + \delta_t + \underbrace{u_{jt}^{X} - \frac{\eta_X + 1}{\eta_D + 1}u_{jt}^{D}}_{u_{jt}}, \tag{12}$$

where $\delta_t = (\eta_X + 1)[\frac{\eta_D}{\eta_D+1}\ln \Phi_t^{D} - \frac{\eta_X}{\eta_X+1}\ln \Phi_t^{X}]$. By construction, $\ln R_{jt}^{D}$ is correlated with error term u_{jt} in equation (12). I estimate the η_X, κ, and δ_t through generalized method of moments (GMM) with instrumental variables for $\ln R_{jt}^{D}$: $(\ln K_{jt}, \ln L_{jt}^{U}, \ln L_{jt}^{S}, \ln E_{jt})$. The instruments are valid given the assumption that plants do not observe u_{jt}^{D} and u_{jt}^{X} when making a decision on inputs.

I identify Φ_t^D by using the CES functional form: $\Phi_t^D = P_t^D (Q_t^D)^{-\frac{1}{\eta_D}}$. The Colombian dataset provides implicit industry-level price index and I measure P_t^D as this index. I measure Q_t^D as share-weighted domestic revenues following Klette and Griliches (1996). Upon recovering Φ_t^D, I identify Φ_t^X through the relationship $\delta_t = (\eta_X + 1)[\frac{\eta_D}{\eta_D+1} \ln \Phi_t^D - \frac{\eta_X}{\eta_X+1} \ln \Phi_t^X]$.

IV.II Stage 2. Estimating Process Parameters

Given structural parameters estimated in Stage 1, I recover skilled and unskilled labor-augmenting productivities (a_{jt}^S, a_{jt}^U) as well as logged material prices p_{jt}^m numerically.[5] I estimate the parameters of controlled Markov process (4) by imposing the model restrictions: innovations to productivities in period t are uncorrelated with the inputs chosen by plants in period $t-1$. Specifically, I approximate the Markov process as a VAR(1) process and estimate parameters via two-step GMM with the following two sets of moment restrictions.

$$E\left(Z_{jt}^1 \otimes \begin{bmatrix} \varepsilon_{jt}^s \\ \varepsilon_{jt}^u \\ \varepsilon_{jt}^m \end{bmatrix} \right) = 0, \tag{13}$$

$$E\left(Z_{jt}^2 \otimes \begin{bmatrix} \varepsilon_{jt}^s \\ \varepsilon_{jt}^u \\ \varepsilon_{jt}^m \end{bmatrix} \right) = 0, \tag{14}$$

, where $Z_{jt}^1 = (1, a_{j,t-1}^S, a_{j,t-1}^U, p_{j,t-1}^m, e_{j,t-1})$ and $Z_{jt}^2 = (\ln K_{jt}, \ln L_{j,t-1}^U, \ln L_{j,t-1}^S, \ln E_{j,t-1}^M)$. The first set of moment restrictions (13) comprises typical VAR orthogonality conditions and the second set (14) comprises the timing assumption of the model.

V Results

In this section, I report the estimates of demand and production parameters as well as transition parameters of skilled and unskilled labor-augmenting productivities. I then

[5] See Appendix B for the detailed procedure.

briefly discuss the relationship among recovered productivities and other observed variables such as revenues and skilled-to-unskilled ratios.

V.I Production and Demand Parameters

The key parameter of interest is the elasticity of substitutions between skilled and unskilled workers ($\frac{1}{1-\rho}$) because it is central to understand how productivity improvements shape skilled-to-unskilled ratios. The estimated elasticity of substitutions between skilled and unskilled workers equals 2.64 as the first column of Table 3 shows. This value is higher than most estimates obtained by using aggregate data. For instance, since Katz and Murphy (1992) estimated the elasticity at 1.4, the following works have estimated the elasticity at values ranging from 1.4 to 2 (See Acemoglu and Autor (2011) and the reference therein). Besides, Fieler, Eslava, and Xu (2018) calibrate the elasticity at 1.6 to 1.8 using the Colombian manufacturing sector spanning from 1982 to 1988. However, my estimate is higher than the values obtained in the previous works because it is possible that the apparel industry which could not be representative to reflect the aggregate manufacturing sector in Colombia. The elasticity greater than one indicates that, all else equal, increases in skilled labor-augmenting productivities result in replacing unskilled workers with skilled workers and that plants with higher skilled labor-augmenting productivities tend to have higher skilled-to-unskilled ratios.

The third column of Table 3 reports the demand elasticities for both domestic and export markets as well as the relative export market size. The estimation results show exporters enjoy two benefits from exporting which induce higher operating profits. First, exporters can charge higher markups for export sales. While the demand elasticity of the domestic market being -5.78, the counterpart of the export market is -4.47. These values imply that plants in the apparel industry in Colombia charge markups over marginal cost by 20.9 percent in the domestic market and 28.8 percent in the export market. Second, exporters face higher demand in the export market. The estimate of κ is 2.3, which suggests *cetris paribus* exporters can earn 2.3 higher revenues.

V.II Transition Process Parameters

Table 4 reports the estimates of transition process parameters. The skilled and unskilled labor-augmenting improvements due to exporting are reported in the last column of Table 4. Both estimates are positive and statistically significant but the effect of exporting on skilled labor-augmenting productivities is larger than that on the unskilled counterpart. While exporting raising skilled labor-augmenting productivity by 21.8 percent, it raises unskilled labor-augmenting productivity by 15.4 percent.

Why does skilled labor-augmenting productivity increases more? Notice that there are several mechanisms whereby exporting has impact on plant-level productivity pointed by De Loecker (2013). The mechanisms involve not only cost-reducing improvements such as production process innovation but demand-inducing improvements such as product innovation, quality upgrading, or learning the preference of foreign consumers.[6] Though both improvements would raise skilled and unskilled labor productivities, skilled workers could have a comparative advantage in the usage of these newly adopted technology or the new knowledges from trade partners.[7] In this way, skilled labor-augmenting productivity could increase more than unskilled labor-augmenting productivity due to exporting and the estimation results indicate that productivity gains from exporting might be realized in a way of newly adopted technology or new idea from trade partners from advanced economies.

In the first three columns of Table 4 display the estimates of effect of $a^S_{j,t-1}$, $a^U_{j,t-1}$, and $p^m_{j,t-1}$ on a^S_{jt}, a^U_{jt}, and p^m_{jt}. They show that both productivities are highly persistent over time. The persistence indicates that changes in skilled and unskilled labor-augmenting productivities influence plant's decision on hiring skilled and unskilled workers persistently. In addition, the persistence can have a significant impact on skill intensity differences between exporters and non-exporters in the long-run. Given that exporting raises skilled labor-augmenting productivity more and skilled labor-augmenting productivity is more persistent, the skilled productivity gains from exporting do not disappear quickly, while unskilled productivity gains doing so. Overall, higher persistence of skilled

[6]This feature arises because researchers typically use deflated revenues as proxy for output. The measured plant/firm-level productivity reflects not only firm-specific cost-reducing technology but firm-specific demand-shifters.

[7]Yeaple (2005) highlights the comparative advantage of skilled workers in the usage of newly innovated technology.

labor-augmenting productivities generates the large differences in relative skilled labor productivities between exporters and non-exporters.

VI Quantitative Implication of Biased Gains from Exporting

This section explores what would have been mean-differences between exporters and non-exporters in skill intensity if exporting raises both productivities equally. For the sake of simplicity and highlight the role of biased productivity gains from exporting, I hold wage rates for skilled and unskilled workers W_{jt}^S, W_{jt}^U and the innovation terms $\epsilon_{jt}^s, \epsilon_{jt}^u$ at the realized values in the counterfactual exercise.[8]

In my counterfactual exercise, I equalize the effect of exporting on skilled and unskilled labor-augmenting productivities: $g_e^s = g_e^u = 0.15$ - productivity gains from exporting are neutral. Then, using the parameter estimates and the innovations, I create the counterfactual skilled and unskilled labor-augmenting productivities $\bar{a}_{jt}^S, \bar{a}_{jt}^U$ for each plant-year observation. I then construct counterfactual relative skilled labor demand $\frac{\bar{L}_{jt}^S}{L_{jt}^U}$ through first order conditions with respect to skilled and unskilled labors and compute the mean difference in skilled-to-unskilled ratios between exporters and non-exporters. In the first row of Table 5,I tabulate the counterfactual and data-driven mean-differences in skill intensity between exporters and non-exporters. Overall, the intensity is lower by 50 percent in the absence of the biased productivity gains from exporting. This considerable drop suggests that the biased productivity gains from exporting are quantitatively important in generating the large differences between exporters and non-exporters. A qualitatively similar results arise when it comes to the median-differences (The second row of Table 5).

Figure 3 further examines the path of skill intensity differences between exporters and non-exporters from 1982 to 1991 under neutral improvements from exporting. The

[8] This exercise, therefore, assumes away the general equilibrium effect that wage rates are also adjusted and determined by labor market equilibrium conditions. For instance, plants with higher skilled labor-augmenting productivity would likely pay higher wages to skilled workers in the labor market equilibrium. This general equilibrium effect offsets the results that I obtain in this counterfactual analysis. Thus, the quantitative importance of biased productivity gains from exporting would be smaller if I take into account for general equilibrium effect.

picture indicates that biased productivity gains from exporting are more quantitative important in shaping the differences between exporters and non-exporters in the later years. Notice that because the skilled labor-augmenting productivity is more persistent than unskilled labor-augmenting productivity, the biased gains from exporting persist in the long-run, generating exporters become more skill intensive in the later years. In contrast, in the counterfactual exercise with the restriction that the effects of exporting on both productivities are the same, exporters have not become more skill intensive over time. Thus, the quantitative importance of biased productivity gains from exporting in shaping skill intensity differences between exporters and non-exporters is larger in the later years.

VII Conclusion

I study the biased productivity gains from exporting in the context of skilled and unskilled labor-augmenting productivities. Skilled and unskilled labor-augmenting productivities drive the plant-level heterogeneity in skill intensity. Therefore, to understand the relationship between exporting and future skilled-unskilled allocation at the plant-level, documenting whether exporting raises one of the productivities more is a reasonable starting point. In this paper, I measured the effects of exporting on future skilled and unskilled labor-augmenting productivities and quantified the importance of the biased gains in producing the skill intensity differences between exporters and non-exporters.

Using data on the Colombian apparel manufacturers, I first documented that skilled-to-unskilled ratios in the data largely deviate from the predictions by the model without factor-augmenting productivities. I further showed that the plant's export status in the previous period is tightly associated with the deviations, which suggests evidence of biased productivity gains from exporting.

Structural estimation in this paper showed that exporting raises future skilled labor-augmenting productivities by 21 percent while unskilled one by 15 percent. The estimate of the elasticity of substitutions between skilled and unskilled workers is 2.6, implying two types are gross-substitutes. Thus, a plant that began exporting in the previous period would likely have higher skill intensity in the following period. When evaluating the quantitative relevance of the biased gains, I find the biased effects of exporting on plant-level productivities explain 51.5 percent of skill intensity differences between exporters and non-exporters.

Tables and Figures

Table 1: Skilled-to-Unskilled Ratios and Relative Wage

	OLS	OLS	OLS	OLS	OLS	OLS	Panel FE
σ	0.2214	0.2193	0.2139	0.2602	0.2915	0.2955	0.2751
	(0.0276)	(0.0266)	(0.0276)	(0.0279)	(0.0285)	(0.0285)	(0.0337)
$\ln K_{jt}$					0.0532	−0.2730	−0.2854
					(0.007)	(0.0712)	(0.1507)
$(\ln K_{jt})^2$						0.0117	0.0110
						(0.0026)	(0.0055)
Constant	✓	✓	✓	✓	✓	✓	✓
Year		✓	✓	✓	✓	✓	✓
Location			✓	✓	✓	✓	
Ownership				✓	✓	✓	✓
R^2	0.0105	0.0248	0.0471	0.0744	0.0818	0.0842	0.0462

Note. The table displays the estimates of the regression equation $\ln \frac{L^S_{jt}}{L^U_{jt}} = \delta_0 + \delta_j + \delta_t + \beta_1 \ln K_{jt} + \beta_2 (\ln K_{jt})^2 - \sigma \ln \frac{W^S_{jt}}{W^U_{jt}} + \xi_{jt}$. Robust standard errors for OLS and plant-clustered standard errors for FE are in parenthesis. R^2 values for panel FE model are overall R^2.

Table 2: Exporting and Non-neutral Productivities

	OLS	Arellano-Bond	Blundell-Bond
Lagged Export	0.1401	0.0805	0.1001
	(0.0428)	(0.0485)	(0.0503)
$\hat{\xi}_{j,t-1}$		0.5650	0.6679
		(0.0519)	(0.0356)

Note. The table reports the estimation results of OLS, Arellano and Bond (1991) dynamic panel approach, and Blundell and Bond (1998) dynamic panel approach. Robust standard errors are in parenthesis. Dependent variable is the residuals from the regression in Table 1, namely $\hat{\xi}_{jt}$.

Table 3: Estimates of Production and Demand Parameters

Parameters	Estimates	Parameters	Estimates	Parameters	Estimates
γ	0.5332	α_L	0.1229	η_D	-5.7816
	(0.0881)		(0.0234)		(0.1383)
ρ	0.6221	α_M	0.8364	η_X	-4.4716
	(0.1050)		(0.0266)		(0.1092)
		α_K	0.0407	κ	2.3162
			(0.0054)		(0.2754)

Note. The table displays the estimates of the production and demand parameters. Standard errors are in parenthesis. Implied elasticity of substitution across labor, material, and capital is $\frac{1}{1-\gamma} = 2.1422$. The implied elasticity of substitution between skilled and unskilled workers is $\frac{1}{1-\rho} = 2.6460$.

Table 4: Estimates of Transition Process

	$a^S_{j,t-1}$	$a^U_{j,t-1}$	$p^m_{j,t-1}$	$e_{j,t-1}$
a^S_{jt}	0.8193	0.0934	-0.0359	0.2180
	(0.0101)	(0.0125)	(0.0074)	(0.0245)
a^U_{jt}	-0.0195	0.7104	0.0663	0.1538
	(0.0064)	(0.0100)	(0.048)	(0.0193)
p^m_{jt}	-0.1461	0.1259	0.9223	0.2190
	(0.0156)	(0.0156)	(0.0142)	(0.0281)

Note. The table displays the estimates of the Markov process parameters in equation (4). Standard errors are in parenthesis. The Markov process is approximated as a VAR(1) process. Constant terms are suppressed.

Table 5: Quantitative Importance of Non-neutral Productivity Improvement from Exporting

	Data: non-Neutral	Counterfactual: Neutral
Mean Differences	0.3420	0.1795 (52.5%)
Median Differences	0.2528	0.0669 (26.4%)

Note. The table displays the observed/counterfactual logged differences between exporters' skilled-to-unskilled ratios and non-exporters' one. In the counterfactual world, skilled and unskilled labor-augmenting productivities respond to the firm's previous export status equally.

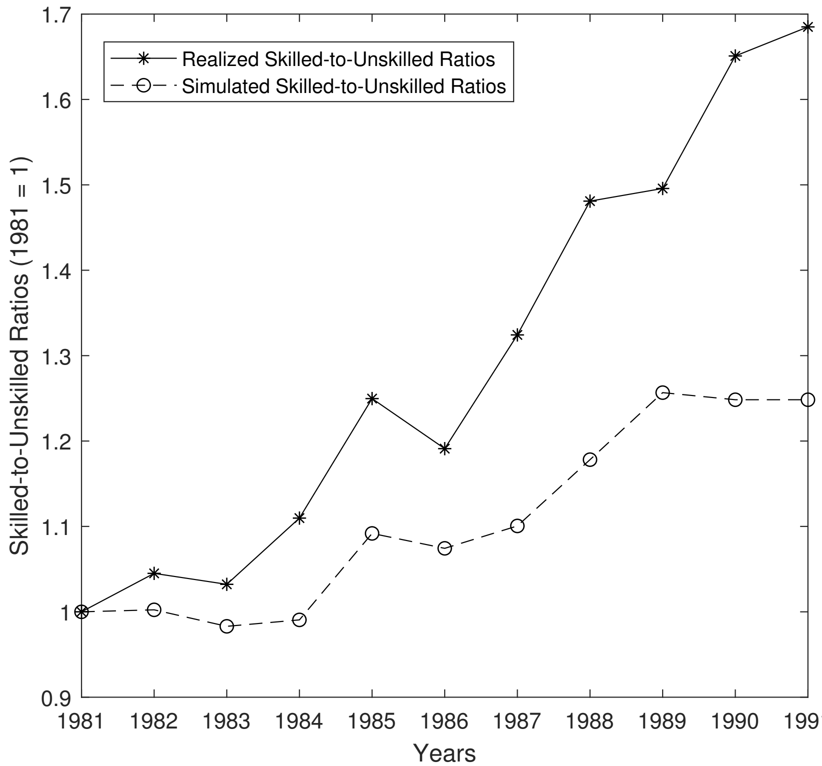

Figure 1: Skilled-to-Unskilled Ratios: Data vs. Simulated

Note. The Figure plots the time evolution of data and simulated skilled-to-unskilled ratios. The solid line displays the realized skilled-to-unskilled ratios and the dashed line displays the simulated counterpart with $\sigma = 0.2955$.

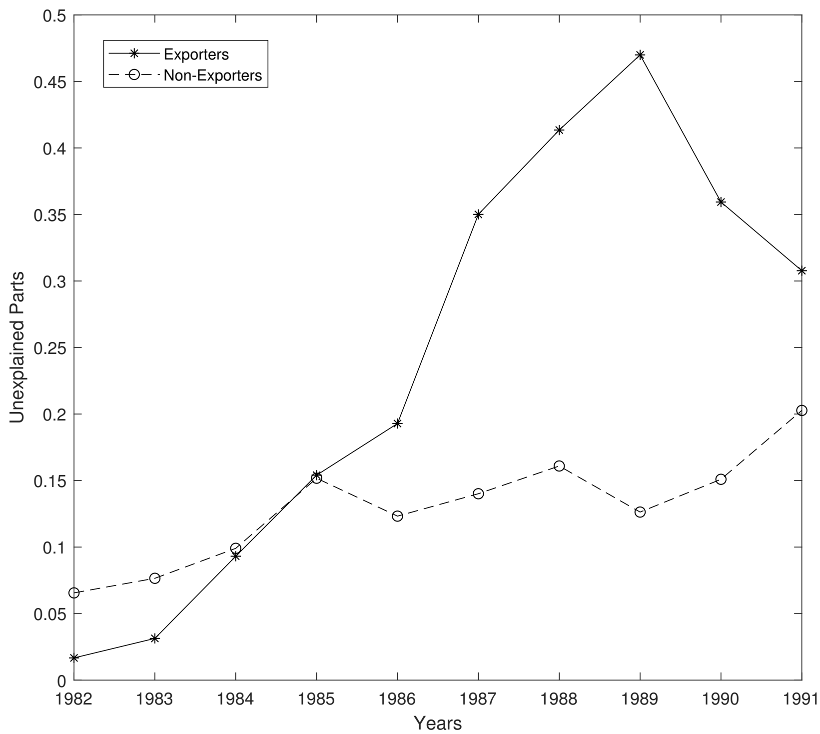

Figure 2: Deviations: Exporter vs. Non-exporters

Note. The Figure plots the time evolution of the deviations computed in Figure 1 for exporters and non-exporters. The solid line displays the series for exporters and the dashed line displays the non-exporters counterparts.

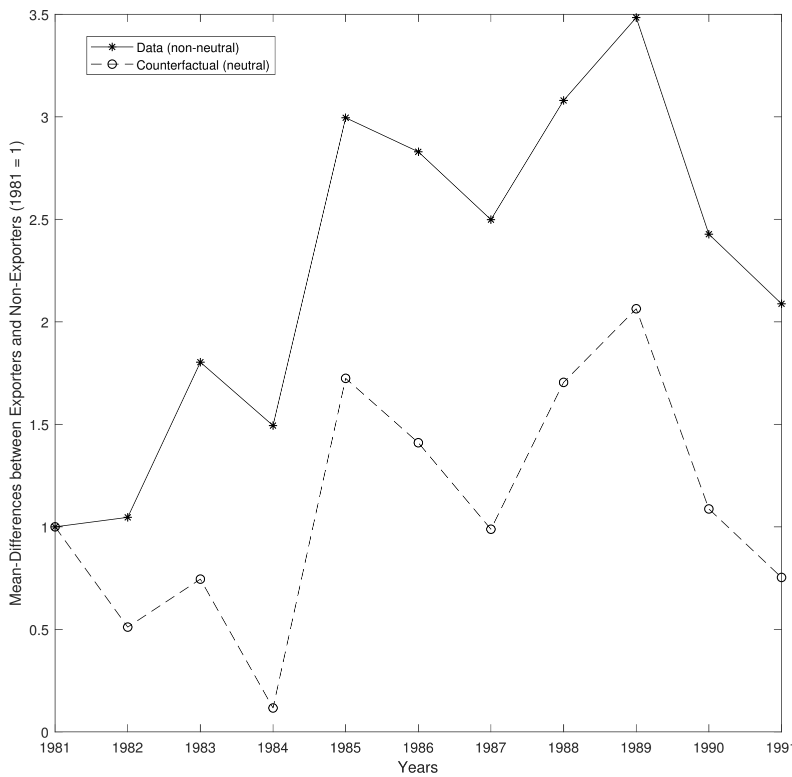

Figure 3: Realized vs. Counterfactual Skill Intensity Differences

Note. The Figure plots the time evolution of the realized and counterfacutal skilled intensity differences between exporters and non-exporters.

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Appendices

A Derivation of Estimating Equations

The first-order conditions of the maximization problem in (5) with respect to skilled labor, unskilled labor, material, output for the domestic market, and output for the export market are as follows:

$$W^S_{jt} = \mu_{jt}\exp(a^S_{jt})[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{\frac{1}{\gamma}-1}\alpha_L(L_{jt})^{\gamma-\rho}(L^S_{jt})^{\rho-1} \tag{A.1}$$

$$W^U_{jt} = \mu_{jt}\exp(a^S_{jt})[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{\frac{1}{\gamma}-1}\alpha_L(L_{jt})^{\gamma-\rho}\exp(\rho\tilde{a}^U_{jt})(L^U_{jt})^{\rho-1} \tag{A.2}$$

$$P^M_{jt} = \mu_{jt}\exp(a^S_{jt})[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{\frac{1}{\gamma}-1}\alpha_M(M^U_{jt})^{\gamma-1} \tag{A.3}$$

$$(\frac{\eta_D+1}{\eta_D})\Phi^D_t(Q^D_{jt})^{\frac{1}{\eta_D}} = \mu_{jt} \tag{A.4}$$

$$\kappa(\frac{\eta_X+1}{\eta_X})\Phi^X_t(Q^X_{jt})^{\frac{1}{\eta_X}} = \mu_{jt}, \text{ provided } e_{jt}=1 \tag{A.5}$$

where μ_{jt} is the Lagrange multiplier corresponding to the production restriction ($Q^D_{jt} + e_{jt}Q^X_{jt} = Q_{jt}$).

I first recover the equation mapping the observables to relative unskilled labor efficiency $\tilde{\nu}_{jt}$. Take ratio with respect to (A.2) and (A.1), I recover $\tilde{a}^U_{jt}$ as a function of observables displayed in (8). Plug back this term into a CES aggregator of skilled and unskilled labors, I arrive at the following equation

$$L_{jt} = (\frac{E^L_{jt}}{E^S_{jt}})^{\frac{1}{\rho}}L^S_{jt}, \tag{A.6}$$

where $E^S_{jt} = W^S_{jt}L^S_{jt}$, $E^U_{jt} = W^U_{jt}L^U_{jt}$, and $E^L_{jt} = E^U_{jt} + E^S_{jt}$.

Second, I can control for unobserved material prices using (A.1), (A.3), and (A.6). Take the ratio with respect to (A.1) and (A.3), and replace L_{jt} with (A.6), I obtain a closed form of M_{jt} as a function of observables.

$$M_{jt} = (\frac{\alpha_L}{\alpha_M}\frac{E^M_{jt}}{E^L_{jt}})^{\frac{1}{\gamma}}(\frac{E^L_{jt}}{E^S_{jt}})^{\frac{1}{\rho}}L^S_{jt}. \tag{A.7}$$

Finally, for plants serving the domestic market only, (A.1) and (A.4) imply

$$\exp(\frac{\eta_D+1}{\eta_D}a^S_{jt}) = (\Phi^D_t)^{-1}[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{1-\frac{1}{\gamma}\frac{\eta_D+1}{\eta_D}}(L_{jt})^{\rho-\gamma}E^S_{jt}(L^S_{jt})^{-\rho}. \tag{A.8}$$

Then, observed domestic revenue R^D_{jt} is

$$\begin{aligned} R^D_{jt} &= \Phi^D_t(Q^D_{jt})^{\frac{\eta_D+1}{\eta_D}}\exp(u^D_{jt}) \\ &= \Phi^D_t(Q^D_{jt})^{-\frac{1}{\eta_D}}\exp(\frac{\eta_D+1}{\eta_D}a^S_{jt})[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{\frac{1}{\gamma}\frac{\eta_D+1}{\eta_D}}\exp(u^D_{jt}). \end{aligned} \tag{A.9}$$

Plug (A.8) into (A.9), I arrive at

$$R^D_{jt} = (\frac{\eta_D}{\eta_D+1})[\alpha_L(L_{jt})^\gamma + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}](L_{jt})^{\rho-\gamma}E^S_{jt}(L^S_{jt})^{-\rho}\exp(u^D_{jt}) \tag{A.10}$$

Replace L_{jt} and M_{jt} with (A.6) and (A.7), I obtain the following estimating equation.

$$\ln R^D_{jt} = \ln\frac{\eta_D}{\eta_D+1} + \ln[E^M_{jt} + E^L_{jt}(1 + \frac{\alpha_K}{\alpha_L}(\frac{K_{jt}}{L^S_{jt}})^\gamma(\frac{E^S_{jt}}{E^L_{jt}})^{\frac{\gamma}{\rho}})] + u^D_{jt}, \tag{A.11}$$

where $E^M_{jt} = P^M_{jt}M_{jt}$.

Use (A.7) and the normalization restriction that the geometric mean of all inputs is one, I obtain the identifying restriction for α_M.

$$\frac{\alpha_M}{\alpha_L} = \frac{\bar{E}^M}{\bar{E}^L}(\frac{\bar{E}^L}{\bar{E}^S})^{\frac{\gamma}{\rho}},$$

where $\bar{E}$ refers to the geometric mean of all expenditures. To identify α_K, I restrict that the sum of distribution parameters is one.

$$\alpha_L + \alpha_M + \alpha_K = 1$$

I estimate the production function parameters including the demand market elasticity through constrained nonlinear least squared (NLLS).

$$\begin{aligned}(\hat{\eta}_D, \hat{\gamma}, \hat{\rho}, \hat{\alpha}_L, \hat{\alpha}_M, \hat{\alpha}_K) &= \arg\min \hat{Q}(\Theta) \\ \text{subject to } \frac{\alpha_M}{\alpha_L} &= \frac{\bar{E}^M}{\bar{E}^L}(\frac{\bar{E}^L}{\bar{E}^S})^{\frac{\gamma}{\rho}}, \\ \text{and } \alpha_L + \alpha_M + \alpha_K &= 1,\end{aligned}$$

where $\Theta = (\eta_D, \theta, \sigma, \alpha_L, \alpha_M, \alpha_K)$, and $\hat{Q}$ is the sample objective function corresponding to (11).

For the derivation of (12), I use equations (A.4) and (A.5). Take the ratio with respect to these equations, I represent Q^X_{jt} as a function of Q^D_{jt}.

$$Q^X_{jt} = (\frac{1}{\kappa}\frac{\eta_X}{\eta_X + 1}\frac{\eta_D + 1}{\eta_D}\frac{\Phi^D_t}{\Phi^X_t})^{\eta_X}(Q^D_{jt})^{\frac{\eta_X}{\eta_D}}. \tag{A.12}$$

Use (6) and (7), I translate (A.12) to

$$\ln R^X_{jt} = -\eta_X \ln \kappa + (\eta_X + 1)\ln(\frac{\eta_X}{\eta_D}\frac{\eta_D + 1}{\eta_X + 1}) + \frac{\eta_X + 1}{\eta_D + 1}\ln R^D_{jt} + \delta_t + u_{jt}, \tag{A.13}$$

where $u_{jt} = u^X_{jt} - \frac{\eta_X+1}{\eta_D+1}u^D_{jt}$.

B Recovering Unobservables

Use equation (A.7) to obtain the amount of material M_{jt}. Then, by dividing E^M_{jt} by the recovered M_{jt}, I recover the material prices P^M_{jt}.

I use (A.1), (A.4), and (A.12) to recover skilled labor-augmenting efficiencies. I first use (A.12) and obtain

$$Q_{jt} = Q^D_{jt} + e_{jt}(\frac{1}{\kappa}\frac{\eta_X}{\eta_X + 1}\frac{\eta_D + 1}{\eta_D}\frac{\Phi^D_t}{\Phi^X_t})^{\eta_X}(Q^D_{jt})^{\frac{\eta_X}{\eta_D}}, \tag{B.1}$$

where e_{jt} is an indicator of exporting. Then, by the construction of production function, I have

$$Q^D_{jt} + e_{jt}(\frac{1}{\kappa}\frac{\eta_X}{\eta_X + 1}\frac{\eta_D + 1}{\eta_D}\frac{\Phi^D_t}{\Phi^X_t})^{\eta_X}(Q^D_{jt})^{\frac{\eta_X}{\eta_D}} = \exp(a^S_{jt})[\alpha_L L^{\gamma}_{jt} + \alpha_M M^{\gamma}_{jt} + \alpha_K K^{\gamma}_{jt}]^{\frac{1}{\gamma}} \tag{B.2}$$

Use (A.1) and (A.4), I further obtain

$$\exp(a^S_{jt}) = \frac{\eta_D + 1}{\eta_D}\frac{1}{\alpha_L}L^{\rho-\gamma}_{jt}(L^S_{jt})^{-\rho}E^S_{jt}(\Phi^D_t)^{-1}(Q^D_{jt})^{-1}[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{1-\frac{1}{\gamma}} \tag{B.3}$$

Thus, the equations (B.2) and (B.3) constitute a nonlinear simultaneous equations with two unknowns (a^S_{jt}, Q^D_{jt}). I can solve for these two unknowns numerically.

Finally, I obtain a^U_{jt} using recovered a^S_{jt} and recovered $\tilde{a}^U_{jt}$.

$$\begin{aligned} a^U_{jt} &\equiv a^S_{jt} + \tilde{a}^U_{jt} \\ &= a^S_{jt} + \frac{1}{\rho}\ln\frac{E^U_{jt}}{E^S_{jt}} + \ln\frac{L^S_{jt}}{L^U_{jt}}. \end{aligned} \tag{B.4}$$