Factor-Biased Efficiency Gains from Exporting: Evidence from Colombia

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Abstract

This study examines whether exporting enhances efficiency and favors specific inputs. We develop a production function model within a dynamic exporting and investment framework, capturing factor-biased technical changes. Using Kalman filtering to address measurement error and propensity score matching to control for self-selection into exporting, we analyze Colombia's manufacturing sectors from 1981 to 1991. New exporters achieve a 4% annual increase in labor-augmenting and unskilled labor relative productivity, with no change in Hicks-neutral productivity. Unskilled labor-augmenting productivity grows by 8% annually, aligning with machinery asset expansion, while TFP rises by 3% per year.

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1. Introduction

Exporting plants in both developed and developing nations often achieve significant technology upgrades, becoming larger and more productive than domestic counterparts. Stringent quality standards and exposure to advanced technologies and foreign markets drive investments in machinery, staff training, and production improvements[1]. This paper investigates whether exporting enhances efficiency and whether productivity gains are biased toward skilled or unskilled workers. Such factor-biased gains can increase demand for specific labor types, potentially amplifying wage inequality, altering input allocation across plants, and carrying profound implications for economic inequality, productivity analysis, and production structures.

To estimate these productivity gains, we adopt a production function approach rooted in a dynamic model of exporting and investment that explicitly incorporates factor-biased technical changes. Departing from traditional studies that focus on aggregate total factor productivity effects[2], our framework models plant-level productivity as a set of factor-specific efficiencies that evolve endogenously in response to past exporting and investment decisions. We introduce a novel estimator to jointly identify the production function parameters and the evolution of these factor-augmenting efficiencies, making it applicable to standard production datasets. By integrating these productivity estimates with export decisions, we evaluate the impact of exporting on plant-level efficiency.

Specifically, we estimate a nested constant elasticity of substitution (CES) production function that integrates materials, capital, and composite labor, with composite labor modeled as a CES combination of skilled and unskilled labor. This specification allows us to identify three dimensions of firm productivity: Hicks-neutral, labor-augmenting, and

[1]For a comprehensive review, see Verhoogen (2023). Key studies include Bajgar and Javorcik (2020), Alfaro-Urena, Manelici, and Vasquez (2022), Giorcelli (2019), Lileeva and Trefler (2010), Aw, Roberts, and Xu (2011), Bustos (2011), and Aghion et al. (2018).

[2]See, for example, Clerides, Lach, and Tybout (1998), De Loecker (2007), Aw, Roberts, and Xu (2011), De Loecker (2013), and Garcia-Marin and Voigtländer (2019).

unskilled labor relative productivity. Identification of the production function parameters relies on standard timing assumptions for input choices and variations in non-salary benefits for skilled and unskilled workers. To disentangle Hicks-neutral productivity from measurement error, we reformulate the production function and its associated productivity process as a linear state-space model, applying the Kalman filter—a widely used time-series technique—for signal extraction.

Using the retrieved productivity estimates, we address self-selection into export markets via Propensity Score Matching (PSM) techniques (Rosenbaum and Rubin 1983; Heckman, Ichimura, and Todd 1997) to evaluate how exporting affects productivity. Specifically, we pair new exporters with non-exporting plants based on the estimated conditional choice probabilities (CCP) of exporting[3]. We then apply a matched difference-in-differences (DiD) approach (De Loecker 2007; Garcia-Marin and Voigtländer 2019) to estimate the dynamic treatment effects of exporting on each dimension of firm productivity.

We analyze data from 19 major manufacturing sectors in Colombia between 1981 and 1991, a period marked by gradual export liberalization alongside import substitution policies (Fieler, Eslava, and Xu 2018). During this time, new exporters experience a 4% annual increase in labor-augmenting and unskilled labor relative productivity, while Hicks-neutral productivity remains unchanged. These findings, coupled with evidence that skilled and unskilled labor are complementary and that exporters tend to be more skill-intensive, suggest that exporting fosters unskilled labor-saving technological advancements. Notably, unskilled labor-augmenting productivity grows by 8% annually, paralleling the expansion of machinery assets. Meanwhile, total factor productivity (TFP)—a cost-weighted average of factor-specific productivity components—rises by 3% per year.

Analyzing the impact of exporting on multiple productivity dimensions reveals dynamics that TFP alone cannot fully capture. For instance, Doraszelski and Jaumandreu (2018) show that Spain's technological change is biased, with labor-augmenting and Hicks-neutral

[3]Productivity microestimates allow us to directly estimate CCP at the plant level from observable characteristics.

productivity equally driving output growth, while Raval (2019) find U.S. labor-augmenting productivity strongly correlates with exports, firm size, and growth. Similarly, Zhang (2019) attribute much of the labor share decline in China's steel industry to non-Hicks-neutral technical change. Using the same Colombian data, Clerides, Lach, and Tybout (1998) find no significant impact of exports on plant productivity, proxied by average variable costs and output per worker, highlighting the challenges of identifying export-related efficiency gains[4]. Their findings provide a useful benchmark for our analysis.

The main finding of this paper is that focusing solely on TFP and Hicks-neutral productivity changes overlooks significant effects on non-Hicks-neutral efficiency. While prior studies attribute TFP gains to new technologies adopted by exporters (Bustos 2011; Lileeva and Trefler 2010; Garcia-Marin and Voigtländer 2019), our results reveal that these upgrades disproportionately enhance the plant's efficiency for specific factors—in our case, unskilled workers. This highlights the need to examine factor-biased technical changes after export entry or policy interventions to fully understand their broader implications.

Second, this study contributes to the production function literature by introducing a novel approach to address output measurement errors. Traditional methods treat measurement error as the residual from a nonparametric regression of output on production factors and a productivity proxy. However, these approaches rest on strong assumptions. For instance, techniques using materials or energy (Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015) assume that firms fully observe their productivity when allocating variable inputs, while those relying on investment (Olley and Pakes 1996) require a low incidence of zero-investment observations[5]. By employing a Kalman filter, we relax these assumptions, enabling the correction of output measurement errors using only the panel and cross-sectional variation in the data.

[4]The literature on exports and productivity reports mixed findings, with positive effects in some studies (Bigsten et al. 2004; Van Biesebroeck 2005; Alvarez and López 2005; Blalock and Gertler 2004; De Loecker 2007; Park et al. 2010; Atkin, Khandelwal, and Osman 2017; Garcia-Marin and Voigtländer 2019) but limited evidence in others (Bernard and Jensen 1999; Aw, Chung, and Roberts 2000; Luong 2013).

[5]Both approaches depend on the *strict monotonicity assumption* (Olley and Pakes 1996).

Finally, our empirical findings shed new light into the relationship between the productivity effects of trade liberalization and export-led industrialization. The co-evolution of unskilled labor-saving productivity and machinery stocks following export entry suggests that Colombia's gradual export liberalization in the 1980s spurred technological advancements that reduced reliance on unskilled labor. While traditional export-led policies often targeted specific industries (Reed 2024), our results show that export tariff liberalization drives broader industrial growth by encouraging the widespread adoption of advanced unskilled labor-saving technologies, with potential distributional consequences for the workforce.

The remainder of this paper is structured as follows. Section 2 presents our theoretical framework and derives the core implications. Section 3 describes the data used in the analysis and highlights pertinent descriptive patterns. Section 4 details how we link the core implications of our model with the data to obtain the structural estimates of interest. Section 5 presents and discusses the key findings. Finally, Section 6 provides the conclusion.

2. Theoretical Framework

This section presents a theoretical framework that integrates a production model featuring factor-augmenting productivities (Doraszelski and Jaumandreu (2018); Harrigan, Reshef, and Toubal (2018); Zhang (2019)) with a dynamic model of exporting and investment (Aw, Roberts, and Xu (2011); Rho and Rodrigue (2016); Grieco, Li, and Zhang (2022)).

Each period, the plant minimizes costs by selecting optimal quantities of skilled labor, unskilled labor, and materials. Upon observing its productivity, the plant evaluates whether to enter the export market in the following period, weighing start-up or continuation costs drawn from a known distribution. Exporting may enhance future efficiency, potentially yielding factor-biased productivity gains. Based on its current state and anticipated export status, the plant also determines whether to invest in physical capital. The capital stock

then evolves into the next period, reflecting the current investment decision under the time-to-build assumption and following a standard capital accumulation process.

2.1. Environment

Technology and Productivity Dynamics – Colombian manufacturing plants produce output (Q_{jt}) using a combination of physical capital (K_{jt}), intermediates (M_{jt}), skilled labor (S_{jt}), and unskilled labor (U_{jt}). The production technology follows a nested constant elasticity of substitution (CES) production function[6]:

$$Q_{jt} = \left[\tilde{\alpha}_K K_{jt}^{\rho} + \tilde{\alpha}_M M_{jt}^{\rho} + \tilde{\alpha}_L (\exp(\omega_{jt}^{L}) L_{jt})^{\rho}\right]^{\frac{1}{\rho}} \exp(\omega_{jt}^{H}) \tag{1}$$

$$L_{jt} = \left[\tilde{\alpha}_S S_{jt}^{\theta} + \tilde{\alpha}_U (\exp(\omega_{jt}^{R}) U_{jt})^{\theta}\right]^{\frac{1}{\theta}} \tag{2}$$

The parameters $\tilde{\alpha}_K$, $\tilde{\alpha}_M$, $\tilde{\alpha}_L$, $\tilde{\alpha}_S$, and $\tilde{\alpha}_U$ denote the non-normalized CES share parameters. The elasticity of substitution among capital, materials, and the labor composite is governed by ρ, while θ captures the elasticity of substitution between skilled and unskilled labor. Factor-augmenting productivity for labor is expressed as ω_{jt}^{L}, with ω_{jt}^{R} indicating the relative productivity of unskilled workers compared to skilled workers. Lastly, ω_{jt}^{H} represents the Hicks-neutral productivity term[7].

We assume that the productivity terms evolve as independent Markov processes, influ-

[6]Another approach models the production function with plants combining a CES aggregation of capital and skilled labor with materials and unskilled labor (Krusell et al. (2000)). We prefer our specification because it explicitly parameterizes the elasticity of substitution between skilled and unskilled workers, a key focus of our motivation and analysis. Moreover, our specification allows the elasticity of substitution between capital and skilled or unskilled labor to vary flexibly across plants and over time.

[7] The production function builds on a foundational framework that integrates Hicks-neutral productivity and productivity terms augmenting skilled and unskilled labor:

$$Q_{jt} = \left[\tilde{\alpha}_K K_{jt}^{\rho} + \tilde{\alpha}_M M_{jt}^{\rho} + \tilde{\alpha}_L L_{jt}^{\rho}\right]^{\frac{1}{\rho}} \exp(\omega_{jt}^{H})$$

$$L_{jt} = \left[\tilde{\alpha}_S \left(\exp(\omega_{jt}^{S}) S_{jt}\right)^{\theta} + \tilde{\alpha}_U \left(\exp(\omega_{jt}^{U}) U_{jt}\right)^{\theta}\right]^{\frac{1}{\theta}}$$

enced by the plant's export status and investment decisions in the previous period (see Doraszelski and Jaumandreu (2013) and De Loecker (2013)): $\forall X \in (H, L, R)$,

$$\omega_{jt}^{X} = \iota_t + \iota_s + \rho_X \omega_{jt-1}^{X} + \beta_X^{e} e_{jt-1} + \beta_X^{i} i_{jt-1} + \beta_X^{ei} \left(e_{jt-1} \cdot i_{jt-1} \right) + \xi_{jt}^{X} \tag{3}$$

In this setup, e_{jt-1} denotes an export indicator, set to 1 if plant j exported in period $t-1$, and 0 otherwise. Similarly, i_{jt-1} represents an investment indicator, equal to 1 if plant j invested in physical assets during period $t-1$, and 0 otherwise. These indicators control for the influence of trade and investment on productivity. The terms ξ_{jt}^{H}, ξ_{jt}^{L}, ξ_{jt}^{R} capture idiosyncratic productivity shocks that are mean zero, normally distributed, and independent of past productivity levels, export status, and investment status, reflecting the stochastic nature of productivity dynamics.

Plant's Information on Productivity Evolution — Unlike standard approaches (e.g., Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2015)), we assume that plants allocate labor and intermediate inputs within a period under incomplete information about Hicks-neutral productivity, ω_{jt}^{H}, which they eventually observe before deciding on exporting and capital investment. However, when allocating these inputs, plants have complete information about ω_{jt}^{R} and ω_{jt}^{L}.

Output and Input Markets – Our model does not impose any specific assumptions regarding the nature of product market competition faced by the plants. Plants treat the wage rates for skilled and unskilled workers, denoted by W_{jt}^{S} and W_{jt}^{U}, respectively, as given. These rates may vary across plants and over time due to plant-specific or time-specific idiosyncrasies. We model these wage rates as state variables for firm j at time t, evolving through processes not explicitly specified in the empirical model. Finally, we assume the market

Rearranging these equations shows that $\omega_{jt}^{L} = \omega_{jt}^{S}$ and $\omega_{jt}^{R} = \omega_{jt}^{U} - \omega_{jt}^{S}$. The analysis references these relationships in the rest of the paper.

for materials to be competitive.

2.2. Static Inputs Allocation Decision

Given the stock of physical assets at the start of period t, K_{jt}, the wage rates for skilled and unskilled workers, W_{jt}^S and W_{jt}^U, the price of materials, P_{jt}^M, the labor-augmenting productivity, ω_{jt}^L, the relative productivity of unskilled workers to skilled workers, ω_{jt}^R, the plant's conditional expectation of Hicks-neutral productivity, $E_t\left[\exp(\omega_{jt}^H)\right]$, and the current-period export decision, e_{jt}, plant j minimizes costs to determine the optimal quantities of materials M_{jt}, skilled labor S_{jt}, and unskilled labor U_{jt}:

$$
\begin{aligned}
&\min_{M_{jt},S_{jt},U_{jt}} \quad W_{jt}^S S_{jt} + W_{jt}^U U_{jt} + P_{jt}^M M_{jt} \\
&\text{s.t.} \quad E_t[Q_{jt}] \geq (1 - e_{jt})Q^0 + e_{jt}Q^1 \\
&\qquad Q_{jt} = \left[\tilde{\alpha}_K K_{jt}^{\rho} + \tilde{\alpha}_M M_{jt}^{\rho} + \tilde{\alpha}_L(\exp(\omega_{jt}^L)L_{jt})^{\rho}\right]^{\frac{1}{\rho}} \exp(\omega_{jt}^H) \\
&\qquad L_{jt} = \left[\tilde{\alpha}_S S_{jt}^{\theta} + \tilde{\alpha}_U(\exp(\omega_{jt}^R)U_{jt})^{\theta}\right]^{\frac{1}{\theta}}
\end{aligned}
\tag{4}
$$

The first constraint ensures that the plant's expected output, $E_t[Q_{jt}]$, meets the minimum requirements for the domestic market (Q^0) when not exporting, and for both domestic and export markets (Q^1) when exporting.

2.3. Dynamic Export and Investment Decisions, and End of Period

After allocating these inputs, plant j observes its Hicks-neutral productivity, ω_{jt}^H, which allows it to determine the planned output for the period, denoted as Q_{jt}. We assume that knowledge of Q_{jt} is sufficient for the plant to set output prices, regardless of whether it behaves as a price taker or a price maker[8]. We then define $\pi(\Omega_{jt}, e_{jt})$ as the variable profit

[8]In the price-making case, consider, for instance, a widely adopted scenario where each establishment produces a unique, differentiated variety, and the market operates under monopolistic competition. However, our assumption excludes scenarios involving strategic interactions among plants where they can exert market power. Consequently, our model is not suitable for analyzing the levels or changes in competitive behavior

function associated with cost-minimizing input allocations, where

$$\Omega_{jt} = \left(K_{jt}, W_{jt}^{S}, W_{jt}^{U}, P_{jt}^{M}, \exp(\omega_{jt}^{L}), \exp(\omega_{jt}^{R}), \exp(\omega_{jt}^{H})\right). \tag{5}$$

Plant j subsequently decides whether to enter the export market in the next period. This decision entails incurring non-convex costs, denoted as γ_{jt}, which the plant observes before making its choice, but which remain unobserved by the econometrician. These costs are independently drawn from a distribution $G(\cdot|e_{jt})$, which depends on the plant's current export status. Specifically, if the plant is not exporting ($e_{jt} = 0$), it faces start-up costs, which differ from the continuation costs incurred by current exporters ($e_{jt} = 1$). After deciding whether to export, the plant determines the optimal investment level I_{jt} for the current period, considering the convex investment costs $C(I_{jt}, K_{jt})$.

The following Bellman equation represents the ex-ante expected value of plant j, denoted by $EV(\Omega_{jt}, e_{jt})$:

$$EV(\Omega_{jt}, e_{jt}) = \pi(\Omega_{jt}, e_{jt}) + \int_{\gamma_{jt}} \max_{e_{jt+1}} \left\{ EV^{1}(\Omega_{jt}, e_{jt}) - \gamma_{jt}, EV^{0}(\Omega_{jt}, e_{jt}) \right\} \mathrm{d}G(\gamma_{jt}|e_{jt}) \tag{6}$$

The first term, $\pi(\Omega_{jt}, e_{jt})$, captures the flow value, that is, the profit in the current period, while the second term reflects the expected future value of the plant. The plant compares the continuation value of exporting, $EV^{1}(\Omega_{jt}, e_{jt})$, less the non-convex export costs γ_{jt}, with the continuation value of not exporting, $EV^{0}(\Omega_{jt}, e_{jt})$.

The terms EV^{1} and EV^{0} are derived by optimally selecting the level of investment I_{jt}, conditional on the plant's future export decision. These continuation values in period $t + 1$

across plants in the output market.

are given by, $\forall x \in \{0, 1\}$,

$$EV^x(\Omega_{jt}, e_{jt}) = \max_{I_{jt}} \left\{ -C(K_{jt}, I_{jt}) + \beta \int_{\Omega_{jt+1}} EV(\Omega_{jt+1}, e_{jt+1} = x) \mathrm{d}F(\Omega_{jt+1}|\Omega_{jt}, e_{jt}, I_{jt}) \right\} \tag{7}$$
$$\text{s.t.} \quad K_{jt+1} = (1 - \delta)K_{jt} + I_{jt}$$

Here, the plant maximizes the expected future value by considering both the investment cost $C(K_{jt}, I_{jt})$ and the next period discounted future value conditional on its exporting status in the current period. The term $F(\Omega_{jt+1}|\Omega_{jt}, e_{jt}, I_{jt})$ represents the transition probability distribution of the state variables Ω_{jt+1}, conditional on the current state Ω_{jt}, export status e_{jt}, and investment I_{jt}. The capital stock follows a standard accumulation equation where δ is the depreciation rate. The discount factor is β.

Investment Policy Function – Equations (7) indicates that the investment decision depends on the state variables (Ω_{jt}, e_{jt}) and the choice of export status in the subsequent period e_{jt+1}:

$$I_{jt} = \iota(\Omega_{jt}, e_{jt}, e_{jt+1}) \tag{8}$$

Conditional Choice Probability of Exporting – Based on Equation (6), plant j's CCP of exporting in period $t + 1$, given the state variables (Ω_{jt}, e_{jt}), is expressed as:

$$Pr(e_{jt+1} = 1|\Omega_{jt}, e_{jt}) = \int_{\gamma_{jt}} \mathbb{1}\left\{ EV^1(\Omega_{jt}, e_{jt}) - EV^0(\Omega_{jt}, e_{jt}) \geq \gamma_{jt} \right\} \mathrm{d}G(\gamma_{jt}|e_{jt}). \tag{9}$$

Conditioning on the state variables (Ω_{jt}, e_{jt}) does not imply a degenerate probability distribution for export decisions across plants, as the start-up or continuation costs of exporting, γ_{jt}, are independently distributed. This observation has important implications for the selection of non-exporters into the export market. Consider a group of

non-exporting plants that share the same state ($\Omega_{jt}, e_{jt} = 0$) at time t. The likelihood of these plants entering the export market in period $t+1$ depends entirely on the random draws of start-up costs. Thus, conditional on the state ($\Omega_{jt}, e_{jt} = 0$), the decision to export in the subsequent period is effectively random.

End of Period – At the end of each period, we assume that the administrative data compiler records plant j's output value with an i.i.d. mean-zero, normally distributed measurement error, denoted by ε_{jt}:

$$\tilde{Q}_{jt} = Q_{jt} \exp(\varepsilon_{jt}) \tag{10}$$

3. Data and Descriptive Statistics

We utilize data from the Colombian Annual Manufacturing Survey, conducted by the Departamento Administrativo Nacional de Estadística (DANE), covering the years 1981 to 1991. This panel dataset provides comprehensive annual information on various aspects of manufacturing plants, including output performance and production costs[9].

Although the dataset has been widely studied, starting with Roberts (1996) and Roberts and Tybout (1997), no prior research, to our knowledge, has specifically examined factor-specific productivity gains from exporting in this context, especially concerning labor. This paper addresses this gap by leveraging a major feature of the dataset—the separate reporting of employee numbers and payrolls by worker type—which is essential for identifying productivity differences between skilled and unskilled labor. Following Fieler, Eslava, and Xu (2018), we classify skilled labor as those in the "management" (*directivos*), "technicians" (*técnicos*), and "employees" (*empleados*) categories, while unskilled labor is represented by "workers" (*obreros*).

Following Roberts and Tybout (1997), our analysis focuses on plants within 19 key SIC-3

[9]For a more detailed discussion of the data, refer to Roberts (1996).

exporting industries, including sectors such as food processing, textiles, clothing, leather products, chemicals, and machinery.[10] We restrict our sample to establishments employing both skilled and unskilled workers, thus excluding only 7.9% of observations where either employment category is missing or zero. We apply the data-cleaning procedure from Roberts (1996)[11]. This procedure retains only plants operating for at least two consecutive years. After these refinements, the final dataset comprises 48,775 plant-year observations.

We measure plant-level output using the *real value of output* from the Colombian survey. We calculate the beginning-of-period capital stock by subtracting investment from, and adding depreciation to, the book value of structures, machinery, and transportation and office equipment. We observe the expenditure on materials. We also observe the workforce employed and use wage salaries for the expenditure on them.

We deflate output, worker salaries, and material expenditures using the GDP deflator and deflate the capital stock using the investment deflator. To derive the implicit SIC-3 industry-level output price index, we divide plant sales by real output. Using the 1994 Colombian input-output data (Bussolo and Correa 1998), we compute an industry-year-level materials price index as the geometric average of year-specific output price indices across sourcing industries, weighted by their 1994 output flow shares. Finally, we derive the quantity of materials used by dividing material expenditures by this price index.

In Table 1, we compare pooled sample averages of output per worker, capital stock, material expenditure, number of workers, skill ratios, and skill premia between exporters and non-exporters. Exporters make up approximately 13% of the sample. During the sample period, exporters demonstrate 2.8 times higher productivity in terms of output per worker compared to non-exporters. Exporters also allocate significantly more inputs: on average, they hold seven times the capital stock, five times the material expenditure,

[10]These industries correspond to SIC-3 codes: food processing (311/312), textiles (321), clothing (322), leather products (323/324), paper (341), printing (342), chemicals (351/352), plastics (356), glass (362), nonmetal products (369), iron and steel (371), metal products (381), machinery (382/383), transportation equipment (384), and miscellaneous manufacturing (390).

[11]Following Ruhl and Willis (2017), we also remove outlier observations with extreme changes in labor employment and output, resulting in 135 observations dropped.

TABLE 1. Descriptive Statistics: Exporters vs Non-Exporters

	Exporters	Non-Exporters	Difference
Output per Worker*	0.51	0.18	0.34
	(0.02)	(0.00)	(0.02)
Capital Stock*	75.72	12.37	63.35
	(5.19)	(0.63)	(5.23)
Material Expenditure*	379.60	68.24	311.35
	(12.96)	(1.67)	(13.07)
Number of Workers	204.07	51.89	152.18
	(4.09)	(0.61)	(4.13)
Skill Ratios	0.66	0.51	0.15
	(0.01)	(0.00)	(0.01)
Skill Premia	1.94	1.59	0.36
	(0.01)	(0.01)	(0.01)
N. of Observations	6,395	42,380	

NOTE.– The table displays the pooled sample averages of the variables of interest by exporting status and shows the difference in means between the two groups. Variables marked with an asterisk (*) are expressed in deflated billions of Colombian Pesos. The *Number of Workers* is expressed in units. *Skill Ratios* are calculated as the ratio between the skilled and unskilled workforce. *Skill Premia* are computed as the ratio between the annual salary wage rate for skilled workers and that for unskilled workers. Standard deviations appear in parentheses.

and employ four times the workforce of non-exporters. Additionally, exporters exhibit 30% higher skill ratios and pay 22% higher skill premia compared to their non-exporting counterparts.

3.1. Exporters Trajectories

This subsection examines the evolution of key outcomes following exporters' market entry, setting the stage for our analysis of factor-biased productivity gains from trade. First, we look at changes in skill ratios and skill premia, which may signal skill-biased technological change. Next, we explore labor dynamics and shifts in labor composition among exporters. Third, we assess investment patterns and shifts in capital composition that may drive technological progress. Lastly, we evaluate the trends in both domestic and export sales after market entry to gauge the direction of innovation.

We use an event study design to capture the dynamic impacts of exporting, focusing

on plants that began exporting during the sample period and have continued to do so. Our regression model is specified as follows:

$$y_{jt} = \delta_j + \delta_{st} + \sum_{k=-2}^{-B} \tau_k H_{k,jt} + \sum_{k=0}^{F} \phi_k H_{k,jt} + \varepsilon_{jt} \tag{11}$$

where $H_{k,jt}$ equals 1 if plant j at time t is exporting k years since first entry into the export market, δ_j are plant fixed effects, and δ_{st} are sector-time fixed effects.

Before presenting these reduced-form patterns, it is important to emphasize that the event study estimates offer valuable insights but may also have limitations and biases in uncovering the underlying mechanisms. First, estimating the substitution patterns between skilled and unskilled workers is essential to identify the direction of export-induced, factor-augmenting technical change. Second, the possibility of plants self-selecting into exporting suggests that the observed post-export trends could reflect pre-existing dynamics rather than causal effects. These limitations are addressed in detail in Section 4.

Figure 1A shows the trajectories of skill ratios and premia around the time of export market entry. The skill ratio, defined as the number of skilled workers relative to unskilled workers, increases by roughly 7% within four years after export entry, compared to one year before exporting. In contrast, the skill premia, which represents the relative wage rates of skilled to unskilled labor, decreases by about 5%. This suggests that while exporters become more skill-intensive post-entry, the relative wage paid to skilled workers declines slightly.

Furthermore, Figure 1B reveals that the rise in skill ratios is not driven by layoffs of unskilled labor among exporters. In fact, skilled labor grows by about 20% within four years of export entry, while unskilled labor (*obreros*) increases by 10%. This indicates that exporting leads to an overall expansion of both skilled and unskilled workforces, with firms becoming relatively more skill-intensive as they hire more skilled than unskilled workers. Figure 2 shows that the growth in the skilled workforce is primarily attributed

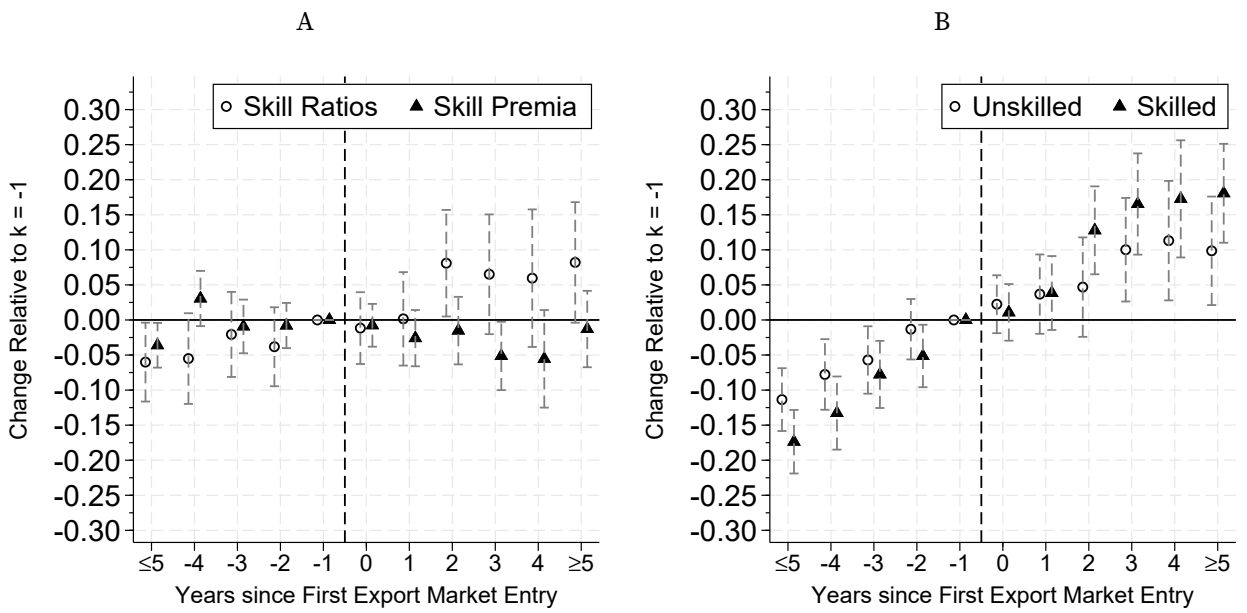


FIGURE 1. Employment Trajectories

This figure displays the coefficients from estimating equation (11) on establishment-level (log) skill ratios and (log) skill premia (Figure 1A) and on (log) skilled labor and (log) unskilled labor (Figure 1B), along with the corresponding 90% robust confidence bounds. The reference subsample consists of firms that started exporting during the sample period, and have stayed in the export market since.

to the *empleados* (employees) category, which increases by 25% over the same period. In contrast, both *directivos* (managers) and *técnicos* (technicians) show more modest growth, around 10% each.

Then, we examine the relationship between exporting and investment (Bustos 2011), followed by an analysis on the changes in domestic and export sales after firms enter the export market. Figure 3 shows that exporters significantly expand their stock of fixed assets upon entering the export market, with investment in machinery and office equipment increasing by about 20%. In contrast, investment in buildings remains more modest and lacks statistical significance. The figure also shows that exporters reduce their holdings of transportation equipment after export entry, though this measurement exhibits considerable noise.

Finally, Figure 4 illustrates the evolution of domestic and export sales after firms enter export markets. Export sales rise significantly, doubling within five years of entry. In

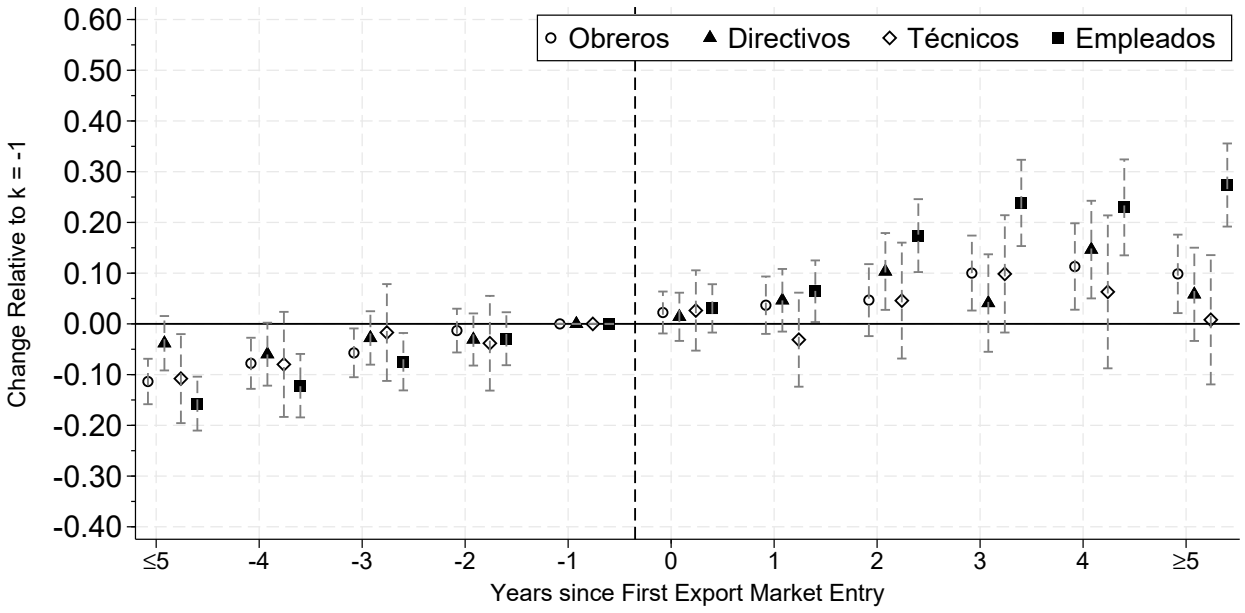


FIGURE 2. Workforce Types Trajectories

This figure shows the coefficients from estimating equation (11) on establishment-level (log) number of *obreros* (workers), *directivos* (managers), *técnicos* (technicians), and *empleados* (employees), along with the corresponding 90% robust confidence bounds. The reference subsample consists of firms that started exporting during the sample period, and have stayed in the export market since.

comparison, domestic sales show significant growth only after five years, increasing by 15% relative to the year of export entry. These trends indicate that production expansion primarily targets export markets.

Overall, we find that exporters increase both sales and investment, consistent with the findings of Bustos (2011) and Garcia-Marin and Voigtländer (2019), while also becoming more skill-intensive. This relationship plays a critical role in shaping the productivity gains from exporting. If exporting plants make unskilled labor-saving investments to enhance output, they may influence productivity gains in a non-neutral way, affecting the skill intensity of production contingent on the underlying technology. This highlights that focusing solely on Hicks-neutral technological change would overlook the full scope of productivity gains from exporting.

Hence, we now turn to the estimation of the production function framework in Section 2, which provides two key advantages. First, it allows us to separately estimate skilled and

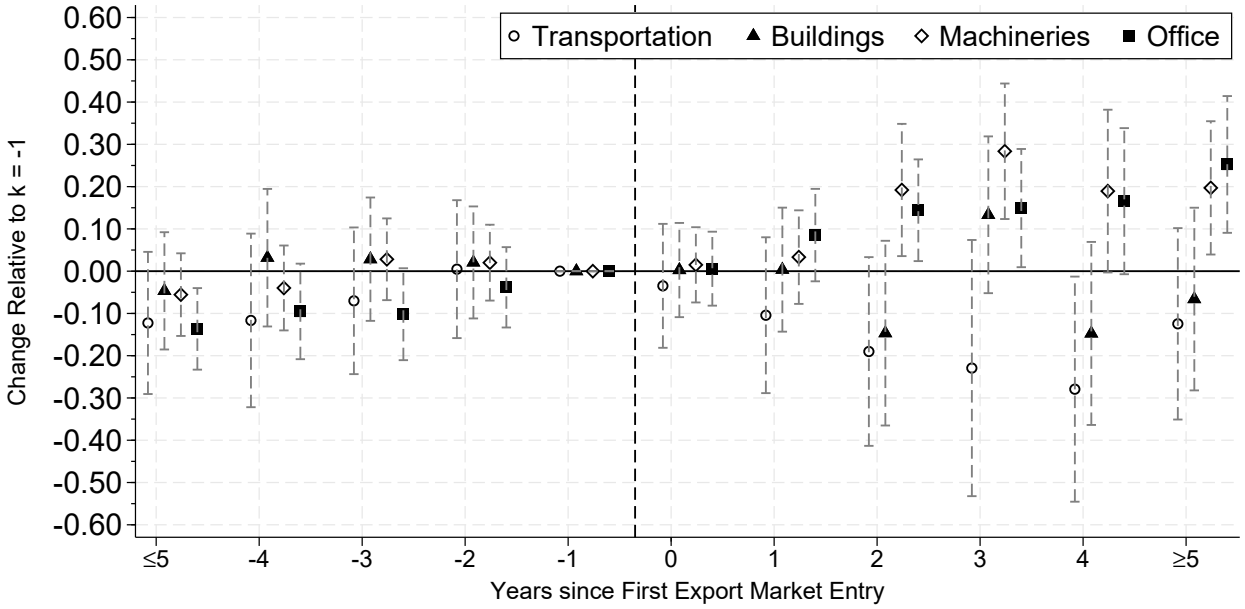


FIGURE 3. Capital Assets Trajectories

This figure shows the coefficients from estimating equation (11) on establishment-level (log) buildings, (log) transportation equipment, (log) machinery holdings, and (log) office equipment, along with the corresponding 90% robust confidence bounds. The reference subsample consists of firms that started exporting during the sample period, and have stayed in the export market since.

unskilled labor-augmenting productivities and the substitution rate between these labor types. Second, it enables precise estimation of the plant's CCP of exporting, allowing us to assess factor-biased productivity gains from trade by comparing exporters with a suitable control group of non-exporters.

4. Empirical Framework

In this section, we proceed as follows. First, we estimate the production function using the Generalized Method of Moments (GMM), incorporating equilibrium conditions and Markovian assumptions for the productivity components. Second, we employ a univariate Kalman filter to distinguish Hicks-neutral productivity from measurement error. Finally, we non-parametrically estimate each plant's CCP of exporting and utilize PSM and DiD methods to compare exporters with comparable non-exporters, assessing the productivity gains from trade.

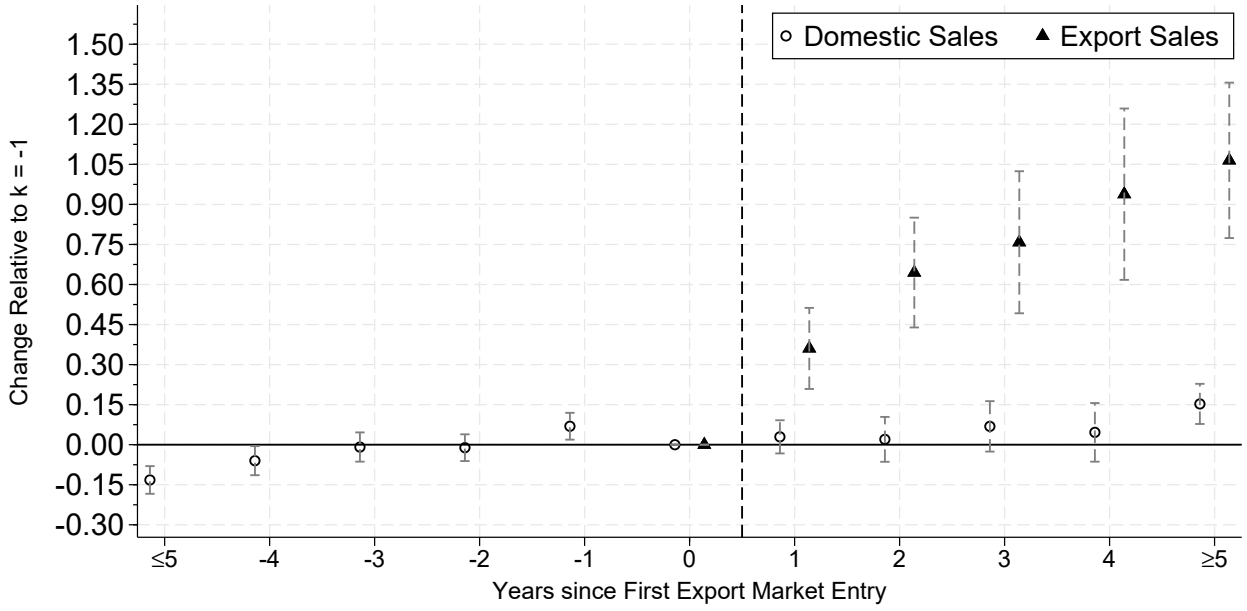


FIGURE 4. Sales Trajectories

This figure presents the coefficients estimated from equation (11) for establishment-level (log) domestic and export sales, along with their 90% robust confidence bounds. The reference subsample includes firms that begin exporting during the sample period and remain active in export markets thereafter. The reference period corresponds to the year the establishment enters the export market.

We adopt the approach of normalizing the CES production function using geometric means[12], following Grieco, Li, and Zhang (2016) and Harrigan, Reshef, and Toubal (2018). Let $\ddot{X}_{jt}$ represent a normalized variable, defined as $\ddot{X}_{jt} = \frac{X_{jt}}{\bar{X}}$, where $\bar{X} = \left(\prod_{n=1}^{N} X_n\right)^{\frac{1}{N}}$. Additionally, let α^X represent the normalized CES share parameters $\forall X \in \{K, M, L, S, U\}$.

Step 1. Estimating θ *and the Markov Process for* $\ddot{\omega}_{jt}^R$ – Let E_{jt}^M represent plant-level expenditures on materials, while E_{jt}^S and E_{jt}^U denote expenditures on skilled and unskilled labor, respectively, with total payroll given by $E_{jt}^L = E_{jt}^S + E_{jt}^U$. By taking the ratio of the first-order conditions from the normalized cost minimization problem (4)[13], we derive the following

[12]Normalizing the production function is crucial for two primary reasons. First, it ensures that the normalized CES share parameters capture the average marginal returns of inputs. Second, it simplifies computation by allowing these parameters to depend on, at most, a single unknown common parameter (see equations (A16)–(A20) in Appendix A). For a comprehensive discussion of the theoretical foundation and implementation of this normalization, please refer to Appendix A.

[13]Refer to the minimization problem in (A22) in Appendix A. Specifically, the first-order conditions (FOCs)

characterization for $\ddot{\omega}^R_{jt}$:

$$\ddot{\omega}^R_{jt} = \frac{1}{\theta}\log\left(\frac{\ddot{E}^U_{jt}}{\ddot{E}^S_{jt}}\right) + \log\left(\frac{\ddot{S}_{jt}}{\ddot{U}_{jt}}\right). \tag{12}$$

Next, we combine (12) with the Markov process for relative productivity of unskilled versus skilled workers (equation (3), normalized[14]), resulting in an estimable equation for θ and the Markov process parameters via GMM. This approach involves concentrating out the Markovian linear coefficients and applying the following moment conditions:

$$\mathbf{m}(\theta) \equiv \mathbb{E}\left(\xi^R_{jt}(\theta) \times Z^R_{jt}\right) = 0. \tag{13}$$

Here, $\xi^R_{jt}(\Theta)$ denotes the forecast error from the Markov process[15], while Z^R_{jt} represents the vector of instruments:

$$Z^R_{jt} = \left(\log\left(\frac{\ddot{B}^S_{jt-1}}{\ddot{B}^U_{jt-1}}\right), \log\left(\frac{\ddot{S}_{jt-1}}{\ddot{U}_{jt-1}}\right)\right)', \tag{14}$$

where $\ddot{B}^S_{jt-1}$ and $\ddot{B}^U_{jt-1}$ represent the normalized non-salary per capita benefits for skilled and unskilled workers at time $t-1$. The exogeneity of these instruments arises from the

---

are given by:

$$E^S_{jt} = \lambda_{jt}E_t[Q_{jt}]\left(\frac{\alpha_L\left(\exp(\ddot{\omega}^L_{jt})\ddot{L}_{jt}\right)^\rho}{\alpha_K\ddot{K}^\rho_{jt} + \alpha_M\ddot{M}^\rho_{jt} + \alpha_L\left(\exp(\ddot{\omega}^L_{jt})\ddot{L}_{jt}\right)^\rho}\right)\left(\frac{\alpha_S\ddot{S}^\theta_{jt}}{\ddot{L}^\theta_{jt}}\right),$$

$$E^U_{jt} = \lambda_{jt}E_t[Q_{jt}]\left(\frac{\alpha_L\left(\exp(\ddot{\omega}^L_{jt})\ddot{L}_{jt}\right)^\rho}{\alpha_K\ddot{K}^\rho_{jt} + \alpha_M\ddot{M}^\rho_{jt} + \alpha_L\left(\exp(\ddot{\omega}^L_{jt})\ddot{L}_{jt}\right)^\rho}\right)\left(\frac{\alpha_U\left(\exp(\ddot{\omega}^R_{jt})\ddot{U}_{jt}\right)^\theta}{\ddot{L}^\theta_{jt}}\right),$$

$$E^M_{jt} = \lambda_{jt}E_t[Q_{jt}]\left(\frac{\alpha_M\ddot{M}^\rho_{jt}}{\alpha_K\ddot{K}^\rho_{jt} + \alpha_M\ddot{M}^\rho_{jt} + \alpha_L\left(\exp(\ddot{\omega}^L_{jt})\ddot{L}_{jt}\right)^\rho}\right).$$

[14]See equation (A21) in Appendix A.

[15]Given an initial guess for θ, equation (12) determines $\ddot{\omega}^R_{jt}(\theta)$. Residuals $\xi^R_{jt}(\theta)$ from the Markov process are obtained by regressing $\ddot{\omega}^R_{jt}(\theta)$ on year and industry fixed effects, $\ddot{\omega}^R_{jt-1}(\theta)$, e_{jt-1}, i_{jt-1}, and $i_{jt-1}e_{jt-1}$.

model's timing assumptions.

Step 2. Estimating ρ *and the Markov Process for* $\ddot{\omega}^L_{jt}$ – Substituting equation (12) into the normalized version of equation (2)[16] and using our estimate for θ, we derive the following characterization for $\ddot{L}_{jt}$:

$$\hat{\ddot{L}}_{jt} = \alpha_S^{\frac{1}{\hat{\theta}}} \ddot{S}_{jt} \left(1 + \frac{E^U_{jt}}{E^S_{jt}}\right)^{\frac{1}{\hat{\theta}}}. \tag{15}$$

By taking the ratios of the FOCs, we obtain:

$$\ddot{\omega}^L_{jt} = \frac{1}{\rho}\log\left(\frac{E^S_{jt}}{E^M_{jt}}\right) + \frac{1}{\rho}\log\left(\frac{\bar{E}^M}{\bar{E}^L}\right) + \log\left(\frac{\ddot{M}_{jt}}{\ddot{L}_{jt}}\right) - \frac{1}{\rho}\log\alpha_S + \frac{\theta}{\rho}\log\left(\frac{\ddot{L}_{jt}}{\ddot{S}_{jt}}\right). \tag{16}$$

Combining equation (16) with (15), our estimate for θ, and the Markov process for labor-augmenting productivity $\ddot{\omega}^L_{jt}$, equation (3) (after normalization[17]), yields an expression to estimate the parameter ρ and the Markov process using GMM.

We first concentrate out the linear Markov coefficients and then minimize the sample analogue of the following moment condition:

$$\mathbf{m}(\rho) \equiv \mathbb{E}\left(\xi^L_{jt}(\rho) \times Z^L_{jt}\right) = 0. \tag{17}$$

Here, $\xi^L_{jt}(\rho)$ denote the forecast errors from the productivity Markov process[18], while Z^L_{jt} represents the vector of instruments derived from the model's timing assumptions:

$$Z^L_{jt} = \left(\log\left(\frac{\ddot{E}^S_{jt-1}}{\ddot{E}^M_{jt-1}}\right)\right)'. \tag{18}$$

[16] See equation (A14) in Appendix A.

[17] See equation (A21) in Appendix A.

[18] Given an initial guess for ρ, equation (16) determines $\ddot{\omega}^L_{jt}(\rho)$. Residuals $\xi^L_{jt}(\rho)$ from the Markov process are obtained by regressing $\ddot{\omega}^L_{jt}(\rho)$ on year and industry fixed effects, $\ddot{\omega}^L_{jt-1}(\rho)$, e_{jt-1}, i_{jt-1}, and $i_{jt-1}e_{jt-1}$.

Step 3. Estimating $(\alpha_K, \alpha_L, \alpha_M)$ *and the Markov Process for* $\ddot{\omega}^H_{jt}$ – We define the CES component of production as:

$$f(\mathbb{\alpha}, \rho, \ddot{X}_{jt}) = \left[\alpha_K \ddot{K}^{\rho}_{jt} + \alpha_M \ddot{M}^{\rho}_{jt} + \alpha_L (\exp \ddot{\omega}^L_{jt} \ddot{L}_{jt})^{\rho}\right]^{\frac{1}{\rho}}, \tag{19}$$

where $\mathbb{\alpha} = (\alpha_K, \alpha_L, \alpha_M)$ and $\ddot{X}_{jt} = (\ddot{K}_{jt}, \ddot{M}_{jt}, \ddot{L}_{jt}, \ddot{\omega}^L_{jt})$. Here, ρ and $\ddot{X}_{jt}$ are either observed in the data or estimated in previous steps.

By combining the normalized production function (1) with equation (10) and the Markov process for Hicks-neutral productivity (3)[19], we obtain the following expression:

$$\begin{aligned} \log \ddot{\tilde{Q}}_{jt} = {} & \ddot{\iota}_t + \ddot{\iota}_s + \log f(\mathbb{\alpha}, \rho, \ddot{X}_{jt}) \\ & + \rho_H \left[\log \ddot{\tilde{Q}}_{jt-1} - \log f(\mathbb{\alpha}, \rho, \ddot{X}_{jt-1})\right] \\ & + \beta^e_H e_{jt-1} + \beta^i_H i_{jt-1} + \beta^{ei}_H (e_{jt-1} \cdot i_{jt-1}) + \chi_{jt}, \end{aligned} \tag{20}$$

where $\ddot{\tilde{Q}}_{jt}$ is the normalized observed output, and $\chi_{jt} = \xi^H_{jt} + \varepsilon_{jt} - \rho_H \varepsilon_{jt-1}$ represents a combination of past and current output measurement errors along with the forecast error in Hicks-neutral productivity.

Equation (20) cannot be directly estimated using least squares because the observed lagged output, $\log \ddot{\tilde{Q}}_{jt-1}$, correlates with past measurement error, ε_{jt-1}. However, under the model's assumptions—including a one-period time-to-build for capital, i.i.d. measurement error from statistical reporting agencies, and the realization of Hicks-neutral productivity after input allocation—$\mathbb{\alpha}$ becomes identifiable via GMM.

Specifically, we estimate $\mathbb{\alpha}$ using GMM subject to the parametric constraints $\alpha_K + \alpha_L + \alpha_M = 1$ and $\bar{E}^L \alpha_M = \bar{E}^M \alpha_L$. First, we concentrate out the linear parameters of the Markov process and then use the following moment condition:

$$\mathbf{m}(\mathbb{\alpha}) \equiv \mathbb{E}\left(\chi_{jt}(\mathbb{\alpha}) \times Z^H_{jt}\right) = 0, \tag{21}$$

[19] Refer to equations (A13) and (A21) in Appendix A.

where Z_{jt}^{H} is the vector of instruments:

$$Z_{jt}^{H} = \left(\log \ddot{K}_{jt-1}, \log \ddot{S}_{jt-1}, \log \ddot{U}_{jt-1}, \log \ddot{M}_{jt-1}, \hat{\ddot{\omega}}_{jt-1}^{L}, \hat{\ddot{\omega}}_{jt-1}^{R}\right)'. \tag{22}$$

At this stage, we are able to estimate only the combination of Hicks-neutral productivity and measurement error, $\widehat{\ddot{\omega}_{jt}^{H} + \varepsilon_{jt}}$. The next step focuses on disentangling these two components.

Step 4. Filtering $\ddot{\omega}_{jt}^{H}$ *and* ε_{jt} – After estimating the parameters of the production function, we derive the micro-level estimate for the CES component:

$$\hat{f}_{jt} = \log f(\widehat{\mathbb{Q}}, \widehat{\rho}, \ddot{X}_{jt}).$$

This allows us to reframe equation (20) as a linear state-space model:

$$\log \ddot{\tilde{Q}}_{jt} = H\pi_{jt} + AY_{jt} + \ddot{\iota}_{t} + \ddot{\iota}_{s}, \tag{23}$$

$$\pi_{jt} = F\pi_{jt-1} + Gu_{jt}, \tag{24}$$

where the measurement equation (23) includes:

$$H = \begin{bmatrix} 1 & 1 & -\hat{\rho}_{H} \end{bmatrix}, \quad A = \begin{bmatrix} \hat{\rho}_{H} & 1 & -\hat{\rho}_{H} & \hat{\beta}_{H}^{e} & \hat{\beta}_{H}^{i} & \hat{\beta}_{H}^{ei} \end{bmatrix},$$
$$Y_{jt} = \begin{bmatrix} \log \ddot{\tilde{Q}}_{jt-1} & \hat{f}_{jt} & \hat{f}_{jt-1} & e_{jt-1} & i_{jt-1} & e_{jt-1}i_{jt-1} \end{bmatrix}',$$

and the transition equation (24) specifies:

$$\pi_{jt} = \begin{bmatrix} \xi_{jt}^{H} & \varepsilon_{jt} & \varepsilon_{jt-1} \end{bmatrix}', \quad u_{jt} = \begin{bmatrix} \xi_{jt}^{H} & \varepsilon_{jt} \end{bmatrix}',$$

$$F = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \quad G = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad \text{var}(u_{jt}) = \Sigma = \begin{bmatrix} \sigma_H^2 & 0 \\ 0 & \sigma_\varepsilon^2 \end{bmatrix}.$$

This framework considers Σ as the only unknown parameters, allowing us to decompose $\ddot{\omega}_{jt}^H$ and ε_{jt} first by estimating $(\sigma_H^2, \sigma_\varepsilon^2)$ and then filtering π_{jt}.

Specifically, assuming that u_{jt} follows an i.i.d. normal distribution with mean zero and variance Σ, we apply the Kalman filter to the state-space representation to estimate $(\sigma_H^2, \sigma_\varepsilon^2)$ by maximizing the conditional likelihood (MLE). Afterward, the Kalman smoother retrieves the estimates of $\ddot{\omega}_{jt}^H$ and ε_{jt}, as detailed in Appendix B.

Step 5. Matched Difference-in-Difference to Estimate Productivity Gains from Exporting – In the final step of our empirical strategy, we analyze productivity dynamics around export entry. One possible approach involves examining the coefficients of the productivity Markov processes (De Loecker (2013)). Controlling for prior productivity helps mitigate self-selection into exporting but may not fully address variations in export effects. For example, the impact of exporting at $t-1$ on productivity at t could differ between firms with established export histories and recent entrants.

In this light, we implement a matched DiD approach, following De Loecker (2007) and Garcia-Marin and Voigtländer (2019), to estimate the local effect of exporting on plants that began exporting during the sample period and continued thereafter[20]. By matching new exporters with similar establishments serving only the domestic market based on their conditional probability of export entry, we account for pre-export differences[21]. This method also captures dynamic effects, such as incremental productivity gains that persist

[20]This excludes plants that continuously exported or exited the export market during the period.

[21]As noted in Section 2, when both plants are in the same state, the decision to export depends solely on the realization of i.i.d. random sunk costs. Under this structural assumption, the matched difference-in-differences technique effectively controls for self-selection bias, as export status becomes a random assignment between these firms.

beyond the initial export entry.

First, we assume that the random start-up or continuation costs of exporting are given by:

$$\gamma_{jt} = \gamma_S(1 - e_{jt}) + \gamma_C e_{jt} + \zeta_{jt}, \tag{25}$$

where ζ_{jt} follows an i.i.d. logistic distribution (0, 1). We then estimate the CCP of exporting for each plant in each year using a flexible dynamic panel logit model:

$$Pr(e_{jt+1} = 1 \mid \ddot{\Omega}_{jt}, e_{jt}) = \mathcal{G}\left(p\left(\hat{\ddot{\vartheta}}_{jt}, e_{jt}, \iota_{It}\right)\right), \tag{26}$$

where $\mathcal{G}(\cdot)$ represents the cumulative distribution function of the logistic distribution (0, 1), p is a first-order polynomial, $\hat{\ddot{\vartheta}}_{jt}$ is the log-transformation of the state estimates $\hat{\ddot{\Omega}}_{jt}$, and ι_{It} is an industry-year-specific fixed effect that accounts for systematic differences in export demand and cost conditions across industries.

Second, we use the estimated CCPs as propensity scores to match each new exporter, in the year before they enter the export market, with a control group of never-exporting plants. Using the nearest neighbor PSM technique (Rosenbaum and Rubin (1983), Heckman, Ichimura, and Todd (1997)), we select five never-exporting plants within the same 3-digit SIC industry that have propensity scores similar to those of each new exporter.

Finally, we assess the dynamic impacts of exporting on productivity by calculating the differences in productivity growth rates between new exporters and their matched never-exporting counterparts at each period h before and after export entry:

$$\tau_h = \frac{1}{N_T}\sum_j \left[(y_{j,t_j+h} - y_{j,t_j-1}) - \frac{1}{|\mathcal{C}_j|}\sum_{l\in\mathcal{C}_j} w_{jl}(y_{l,t_l+h} - y_{l,t_l-1})\right], \tag{27}$$

where y represents the outcome of interest, $\mathcal{C}_j$ denotes the set of never-exporting plants matched to new exporter j via PSM, w_{jl} is the weight assigned to each matched observation

l, and t_j indicates the year in which firm j starts exporting.

5. Results and Discussion

5.1. Estimates of the Production Function Model Parameters

Table 2 presents the baseline estimates of the production function parameters. The results reveal that skilled and unskilled labor act as gross complements in Colombian manufacturing sectors during the sample period. The estimated elasticity of substitution, $\frac{1}{1-\theta}$, of 0.49[22] highlights that when the relative productivity of unskilled workers increases (or decreases), plants adjust optimally by decreasing (or increasing) their relative use of unskilled labor, assuming constant relative wages. Importantly, these results suggest that the observed increase in skilled labor intensity among exporters may be driven by productivity gains that specifically enhance the efficiency of unskilled labor.

TABLE 2. Estimates of Production Function Parameters

$\frac{1}{1-\rho}$	$\frac{1}{1-\theta}$	α_L	α_M	α_K	α_S	α_U	σ_H	σ_ε
0.337	0.490	0.190	0.744	0.066	0.320	0.680	0.611	0.328
(0.053)	(0.030)	(0.027)	(0.106)	(0.133)	(0.003)	(0.003)	(0.061)	(0.048)

NOTE.– This table reports the estimates of the model's structural parameters. Standard errors are calculated using a non-parametric bootstrap clustered at the establishment level. We draw 1,000 bootstrap samples with replacement and re-estimate the structural model for each sample. Out of these, 998 simulations successfully converged.

We estimate the outer-nest elasticity of input substitution in our CES model, $\frac{1}{1-\rho}$, at 0.34[23], which indicates strong complementarity between capital, materials, and composite labor. We also recover the CES share parameters, which, under our normalization,

[22] Our findings on the complementarity between skilled and unskilled workers deviate from the consensus elasticity estimate of 1.5 reported in the seminal studies by Katz and Murphy (1992) and Autor, Katz, and Kearney (2008), as well as the average results highlighted in the literature (see the meta-analysis by Havranek et al. (2024)). We present robustness checks for our value in Section 5.4.

[23] This estimate closely aligns with the findings of Raval (2019) and the broader insights from the meta-analysis by Gechert et al. (2022).

represent the average marginal returns of each input. Our results show values of 0.19 for composite labor, 0.74 for materials, and 0.07 for capital[24], as well as 0.32 for skilled labor and 0.68 for unskilled labor. Finally, we estimate the standard deviation of the forecast error for Hicks-neutral productivity, σ_H, at 0.61 and the standard deviation of measurement error, σ_ε, at 0.33, which yields a signal-to-noise ratio of 1.86.

In Table 3, we present the baseline estimates for the coefficients of the Markov productivity processes, each modeled as an AR(1). Each productivity component exhibits high persistence, with autoregressive coefficients of 0.79 for Hicks-neutral productivity, 0.86 for labor-augmenting productivity, and 0.86 for unskilled labor relative productivity. The coefficient on the lagged exporter dummy shows that prior exporting status, on average, increases Hicks-neutral productivity by 5%, labor-augmenting productivity by 7%, and unskilled labor relative productivity by 10%. Moreover, conditional on exporting, investment in buildings, machinery, and office equipment reduces Hicks-neutral productivity by 11%, increases labor productivity by 3%, and raises unskilled labor relative productivity by 9%.

These average effects, however, mask compositional heterogeneity by combining new exporters, who likely experience stronger effects, with continuing exporters, who may show attenuated effects. Additionally, while controlling for prior productivity levels mitigates selection bias (De Loecker (2013)), the control group includes a mix of never-exporters, future exporters, and firms that exited the export market. For these reasons, we now shift our focus to our preferred analysis of local, factor-biased productivity gains from trade specifically for new exporters.

5.2. Local Estimates of Factor-Biased Productivity Gains from Trade

The PSM procedure matches 424 observations of new exporters with 1,828 observations of never-exporters, forming the sample for analysis. Before applying the DiD method to estimate factor-biased productivity gains from trade, we verify that the PSM process

[24]Grieco, Li, and Zhang (2016) report similar estimates for the outer-nest CES share parameters using the same dataset. We discuss additional robustness checks in Section 5.4.

TABLE 3. Estimates of the Productivity Markov Process Coefficients: (1)

	$\ddot{\omega}^H$	$\ddot{\omega}^L$	$\ddot{\omega}^R$
$\ddot{\omega}^H_{-1}$	0.793	-	-
	(0.020)		
$\ddot{\omega}^L_{-1}$	-	0.864	-
		(0.007)	
$\ddot{\omega}^R_{-1}$	-	-	0.858
			(0.004)
e_{-1}	0.045	0.073	0.096
	(0.046)	(0.040)	(0.036)
i_{-1}	-0.110	0.030	0.085
	(0.056)	(0.012)	(0.012)
$e_{-1}i_{-1}$	-0.053	0.014	0.009
	(0.039)	(0.042)	(0.037)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

NOTE.– This table presents the coefficients for the productivity Markov process. Standard errors are computed using a non-parametric bootstrap clustered at the establishment level. We draw 1,000 bootstrap samples with replacement and re-estimate the structural model for each sample. Out of these, 998 simulations successfully converged.

successfully constructs a suitable control group.

Figure 5 presents the estimated propensity scores to export for new exporters one year before exporting, along with their nearest neighbor controls. The similarity in these distributions between new exporters and matched never-exporters indicates that our matched sample satisfies the common support assumption.[25] Summary statistics in Table 4 further confirm that the PSM procedure produces a well-balanced sample, effectively identifying a suitable control group for new exporters. We detect no statistically significant differences in the relevant state variables between new exporters and matched never-exporters, validating the robustness of our matching process.

Figure 6 presents the estimated effects of trade on the model's productivity components around the export entry period, derived from the matched DiD estimator in equation (27).

[25]The common support assumption also holds for the remaining four nearest neighbors (see Appendix C).

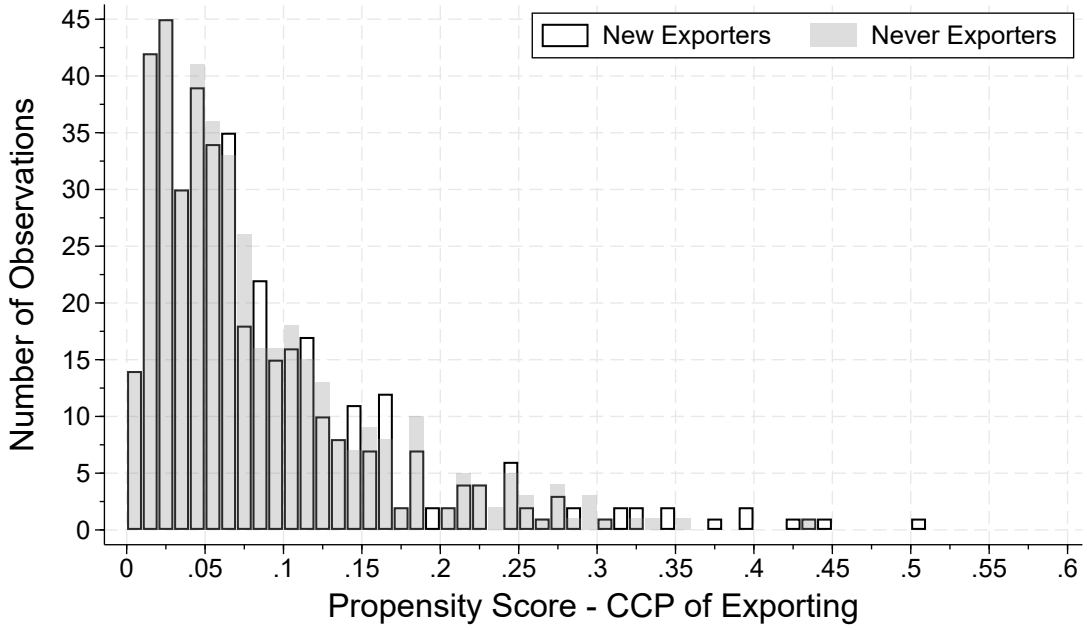


FIGURE 5. PSM Common Support: New Exporters vs Never Exporters

This figure presents histograms of estimated propensity scores (CCP of exporting) for new exporters one year prior to exporting and for their nearest neighboring control plants. Clear bars show the frequency of new exporter observations, while shaded bars represent the frequency of matched never-exporter observations.

TABLE 4. Matching Balancedness: New Exporters vs Never Exporters

	New Exporters	Matched Never Exporters	Difference	t stat	p value
$\log \ddot{K}_{jt-1}$	0.621	0.462	0.159	1.26	0.21
$\log \ddot{W}^{S}_{jt-1}$	0.150	0.116	0.034	0.98	0.33
$\log \ddot{W}^{U}_{jt-1}$	0.028	0.011	0.017	0.64	0.52
$\log \ddot{P}^{M}_{jt-1}$	-0.045	-0.044	0.000	-0.02	0.98
$\ddot{\omega}^{H}_{jt-1}$	0.093	0.114	-0.020	-0.30	0.77
$\ddot{\omega}^{S}_{jt-1}$	0.491	0.468	0.023	0.17	0.87
$\ddot{\omega}^{R}_{jt-1}$	0.306	0.190	0.116	0.85	0.40
Matched Individual Plants	424	1,828			

NOTE.– This table presents the summary statistics of the matched sample constructed through our propensity score matching procedure. The first two columns display the matched sample averages of the normalized state variables by treatment status. The last three columns show the difference in means between the two groups, along with the corresponding *t*-statistic and *p*-value.

The results reveal that new exporters achieve a 25% increase in both labor-augmenting and unskilled labor relative productivity within four years of export entry, corresponding to an annual growth rate of 4%. In contrast, Hicks-neutral productivity shows no change during this period.

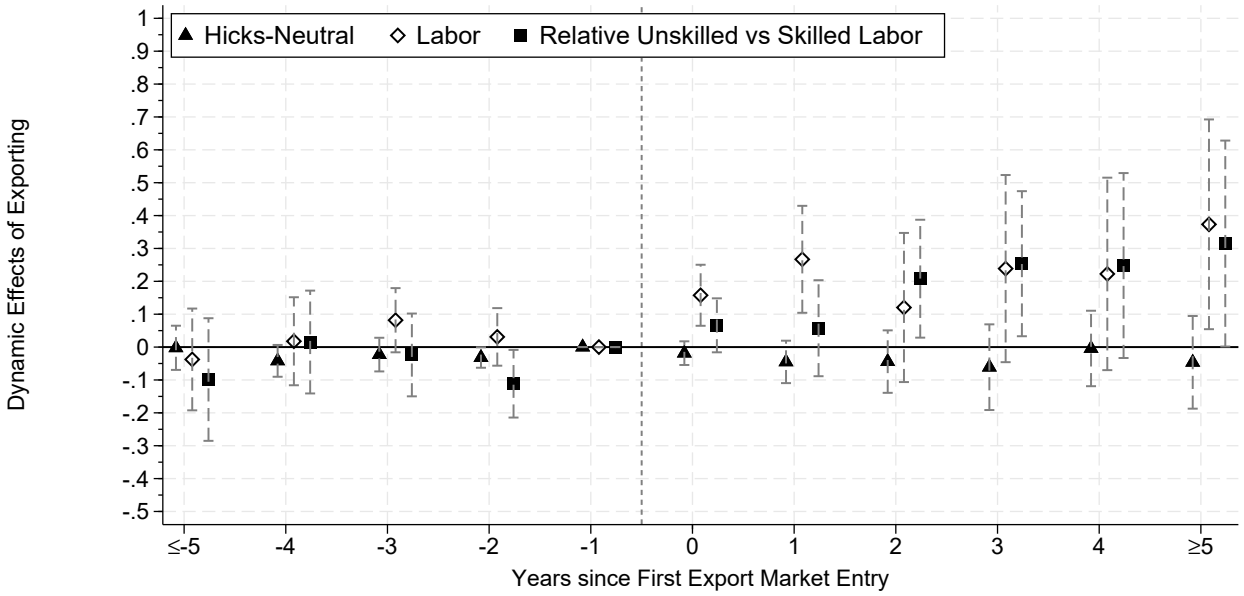


FIGURE 6. Estimated Local Effects of Exporting

This figure displays the estimated effects of exporting on Hicks-neutral productivity, labor-augmenting productivity, and unskilled labor relative productivity, each with 90% Abadie and Imbens (2016) robust confidence intervals. Results remain virtually unchanged when using non-parametrically bootstrapped confidence intervals (Figure D1 in the Appendix).

5.3. Mechanism - Unskilled Labor-Saving Technology Upgrading

Our estimates reveal that new exporters achieve significant productivity gains after entering the export market, driven primarily by increases in labor-augmenting and unskilled labor productivity relative to skilled labor. The strong complementarity between skilled and unskilled labor, coupled with the observed rise in skill intensity among exporters, suggests that exporting fosters unskilled labor-saving technological progress. To reinforce this interpretation, this subsection examines the co-evolution of machinery and equipment

stock alongside unskilled labor-augmenting productivity and TFP.

We reformulate the model so that labor-augmenting productivity equals skilled labor-augmenting productivity in levels, denoted as $\ddot{\omega}^{S}_{jt}$ (see Footnote 7). Using this reformulation, we derive unskilled labor-augmenting productivity in levels as:

$$\ddot{\omega}^{U}_{jt} = \ddot{\omega}^{R}_{jt} + \ddot{\omega}^{S}_{jt}. \tag{28}$$

Then, we compute TFP by taking a cost-weighted average of factor productivities:

$$TFP_{jt} = \log\left(\frac{\ddot{E}^{S}_{jt}}{TVC_{jt}}\exp(\ddot{\omega}^{S}_{jt}) + \frac{\ddot{E}^{U}_{jt}}{TVC_{jt}}\exp(\ddot{\omega}^{U}_{jt}) + \frac{\ddot{E}^{M}_{jt}}{TVC_{jt}}\exp(\ddot{\omega}^{H}_{jt})\right), \tag{29}$$

where $TVC_{jt} = \ddot{E}^{S}_{jt} + \ddot{E}^{U}_{jt} + \ddot{E}^{M}_{jt}$ represents a measure of total variable costs.

Figure 7 displays the matched DiD estimates for TFP, unskilled labor-augmenting productivity, and machinery equipment stock. Aligning with prior studies on the complementarity between exporting and technological upgrading (Bustos 2011; Garcia-Marin and Voigtländer 2019), the findings show that new exporters expand their machinery stock by 60% more than comparable control plants within the first four years after export entry. This surge in machinery assets parallels an equally significant rise in unskilled labor-augmenting productivity, averaging 8% annually over the same period.

We find that exporting increases TFP by 15% in the four years following export entry, equivalent to an annual growth rate of 3%. For Hicks-neutral productivity, our results align with previous studies (Clerides, Lach, and Tybout 1998), which found no effect of exporting on marginal cost proxies and concluded that exporting does not affect plant productivity. However, by accounting for factor-specific productivities and redefining TFP, we show that exporting primarily drives TFP gains through non-Hicks-neutral effects, offering a deeper understanding of export-induced efficiency improvements.

Our findings suggest that new exporters upgrade their production technology by in-

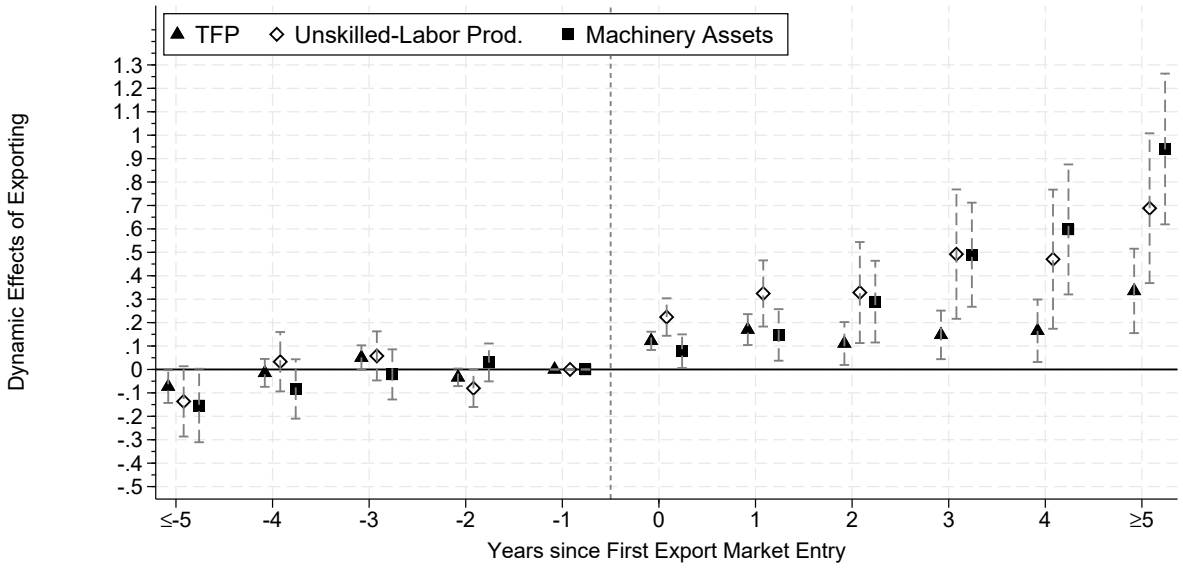


FIGURE 7. Estimated Local Effects of Exporting

This figure displays the local effects of exporting on TFP, unskilled labor-augmenting productivity, and the stock of machinery equipment, along with 90% Abadie and Imbens (2016) robust confidence intervals. Results remain virtually unchanged when using non-parametrically bootstrapped confidence intervals (Figure D2 in the Appendix).

vesting in unskilled labor-saving innovations, such as advanced machinery, which drives both overall productivity gains and improvements biased toward unskilled labor. As new exporters become relatively more productive with unskilled labor than skilled labor, they tend to increase their skilled labor hiring due to the strong complementarity between skilled and unskilled labor in production.

Overall, it appears that export-induced investments in machinery and equipment primarily drive unskilled labor-saving technological progress. Interpreting the effects of exporting solely as a Hicks-neutral TFP shifter risks overlooking these substantial gains in unskilled labor productivity. This perspective sheds new light on the limited empirical evidence of productivity effects from exporting, as previous studies may have overlooked significant factor-augmenting productivity improvements triggered by export activities. We conclude that focusing exclusively on TFP while ignoring non-Hicks-neutral productivity changes leads to an underestimation of the true impact of exporting on plant productivity.

5.4. Additional Robustness Checks

Skilled-Unskilled Workers Substitution – Our identification strategy for the elasticity of substitution between skilled and unskilled workers relies on the assumption that ω_{jt}^{R} follows a Markov process, combined with standard production timeline assumptions (Doraszelski and Jaumandreu 2018). As part of the robustness analysis, we re-estimate the elasticity of substitution between skilled and unskilled workers using alternative instruments leveraging timing as well as geographical variation across Colombian administrative departments (see Figure E1 in Appendix E) of the skill premium.

Specifically, by combining the characterization equation (12) with the normalized Markov process (3), we derive a specification that enables the direct estimation of the elasticity of substitution between skilled and unskilled workers (coefficient b_1) using least squares techniques:

$$\log\left(\frac{\ddot{S}_{jt}}{\ddot{U}_{jt}}\right) = b_1 \log\left(\frac{\ddot{W}_{jt}^{U}}{\ddot{W}_{jt}^{S}}\right) + b_2 \log\left(\frac{\ddot{S}_{jt-1}}{\ddot{U}_{jt-1}}\right) + b_3 \log\left(\frac{\ddot{W}_{jt-1}^{U}}{\ddot{W}_{jt-1}^{S}}\right) + b_4 e_{jt-1} + b_5 i_{jt-1} + b_6\left(e_{jt-1}\cdot i_{jt-1}\right) + i_t + i_s + u_{jt}. \tag{30}$$

To address the endogeneity of contemporaneous relative wages, we use the following instruments: (i) the log-change in the relative wage of skilled to unskilled workers between $t-1$ and $t-2$; (ii) the log-change in skilled worker wages over the same period; (iii) the mean log relative wage of unskilled to skilled workers in $t-1$ across all plants in the same SIC3 industry and administrative department of plant j, excluding plant j, weighted by output; (iv) the mean log relative wage in $t-1$ for plants in the same SIC3 industry of plant j, but from a contiguous department, weighted by output; (v) The interaction between industry-specific skill intensity in $t-4$ for plant j's department, relative to the departmental mean, and the national industry-wide growth in skill intensity, aggregated across industries (Raval 2019; Oberfield and Raval 2021); and (vi) the interaction of national

industry wage premia with the gap between predicted and observed industry-specific skill intensity for plant j's department, relative to the departmental mean, aggregated across industries (Raval (2019); Oberfield and Raval (2021)).

Table 5 presents the two-stage least squares (2SLS) estimates for the elasticity of substitution between skilled and unskilled workers. The results closely align with our baseline estimates in Table 2 and consistently indicate that skilled and unskilled workers are complements in our setting.

CES Share Parameters – Our second robustness check involves calibrating the outer nest CES share parameters outside the model and comparing them to our estimates. We define the total user cost of capital as:

$$E_{jt}^K = \sum_i (r_t + \delta_i) K_{jt}^i \tag{31}$$

where r_t represents Colombia's real interest rate, sourced from the World Bank WDI database[26]. The term δ_i denotes constant depreciation rates by asset type[27], sourced from Roberts (1996), and K_{jt}^i refers to the initial deflated book value of asset i.

Assuming E_{jt}^K represents capital expenditure, our normalization permits the direct computation of the outer nest share parameters[28]. Table 6 presents results closely matching our baseline estimates in Table 2. However, we prioritize the baseline estimates because they are derived from estimation rather than this approximation.

Unfiltered $\ddot{\omega}_{jt}^H$ – In Figure 8, we evaluate whether the local estimates of the effect of exporting on new exporters hold when using the unfiltered measure of Hicks-neutral productivity. Using the same matched sample, we find that results remain consistent whether we use the filtered or unfiltered measure of Hicks-neutral productivity and their accordingly constructed TFP measures. The unfiltered measure, as expected, introduces slightly more

[26] For years before 1986, we substitute the 1986 value due to missing data.

[27] Structures, machinery, office, and transportation equipment.

[28] See Appendix A and equations (A18)–(A20) for the special case $\tau = \frac{\bar{E}_K}{\bar{E}_M}$.

TABLE 5. Robustness - 2SLS Results

	OLS	IV (i)	IV (ii)	IV (iii)	IV (iv)	IV (v)	IV (vi)
$\log\left(\frac{\ddot{W}^U_{jt}}{\ddot{W}^S_{jt}}\right)$	0.346	0.294	0.423	0.498	0.797	0.417	0.480
	(0.012)	(0.052)	(0.100)	(0.233)	(0.441)	(0.246)	(0.288)
First Stage							
$\Delta \log\left(\frac{\ddot{W}^U_{jt-1}}{\ddot{W}^S_{jt-1}}\right)$		-0.179					
		(0.006)					
$\Delta \log \ddot{W}^S_{jt-1}$			0.110				
			(0.008)				
$\sum_{\substack{i\neq j,\\ i\in r\cdot s(j)}} w_{it-1} \log\left(\frac{\ddot{W}^U_{it-1}}{\ddot{W}^S_{it-1}}\right)$				0.052			
				(0.009)			
$\sum_{\substack{i\in a(r(j)),\\ i\in s(j)}} w_{it-1} \log\left(\frac{\ddot{W}^U_{it-1}}{\ddot{W}^S_{it-1}}\right)$					0.022		
					(0.007)		
$\sum_s s_{rs,t-4} g_{st} \left(\frac{\ddot{S}_{st}}{\ddot{U}_{st}}\right)$						-0.051	
						(0.009)	
$\sum_s \nu_{st}(\hat{s}_{rs,t} - s_{rs,t-4})$							0.001
							(<0.001)
F-stat		769.50	210.33	30.48	10.71	29.87	20.25
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	40,351	31,927	31,927	39,862	37,892	40,351	40,351

NOTE.– This table presents the 2SLS estimation results for equation (30), alongside OLS estimates for comparison. The analysis focuses on the coefficient of normalized relative wages, b_1, instrumented using: (i) the log-change in the relative wage of skilled to unskilled workers between $t-1$ and $t-2$; (ii) the log-change in skilled worker wages over the same period; (iii) the mean log relative wage of unskilled to skilled workers in $t-1$ across all plants in the same SIC3 industry and administrative department of plant j, excluding plant j, weighted by output; (iv) the mean log relative wage in $t-1$ for plants in the same SIC3 industry of plant j, but from a contiguous department, weighted by output; (v) The interaction between industry-specific skill intensity in $t-4$ for plant j's department, relative to the departmental mean, and the national industry-wide growth in skill intensity, aggregated across industries (Raval 2019; Oberfield and Raval 2021); and (vi) the interaction of national industry wage premia with the gap between predicted and observed industry-specific skill intensity for plant j's department, relative to the departmental mean, aggregated across industries (Raval (2019); Oberfield and Raval (2021)). The table also includes the first-stage coefficient and the Sanderson-Windmeijer F-statistic to evaluate instrument strength. Details on the instrument construction are provided in Appendix F.

TABLE 6. Robustness - CES Share Parameters Calibration

α_L	α_M	α_K
0.198	0.779	0.022

NOTE.– This table reports the results of calibrating the outer nest CES parameters using equation (31) to approximate total capital expenditure.

noise.

Constructing the matched sample using the noisy measure of Hicks-neutral productivity[29] significantly reduces the precision of the estimated effects of exporting on Hicks-neutral productivity. This finding suggests that introducing noise during the matching stage has a substantially greater impact than solely during the difference-in-differences stage. In contrast, the effects on TFP exhibit negligible differences between scenarios.

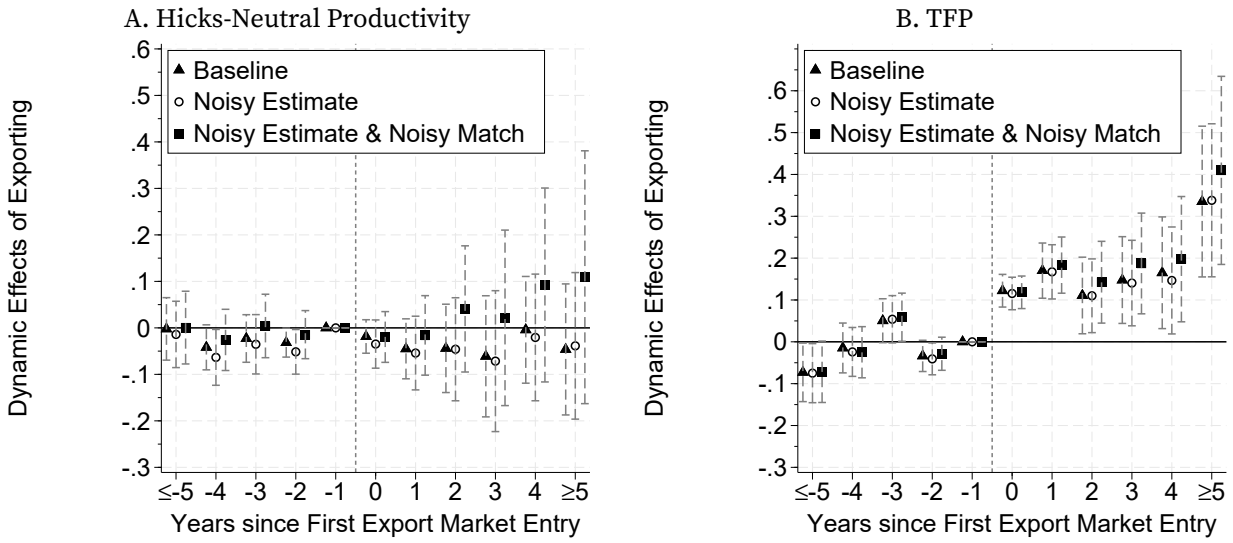


FIGURE 8. Unfiltered $\ddot{\omega}_{jt}^{H}$

This figure illustrates the local effects of exporting on Hicks-neutral productivity and TFP. It compares the baseline results ("Baseline") with two alternative scenarios: one using unfiltered values of Hicks-neutral productivity while maintaining the same matched sample ("Noisy Estimate") and another additionally matching plants based on unfiltered productivity values ("Noisy Estimate & Noisy Match"). The figure also includes robust 90% confidence intervals, following Abadie and Imbens (2016).

Cross-Validation for Kalman Filter – This paper introduces the Kalman filter to disentangle

[29]The matching process results in a balanced sample in terms of observable characteristics and satisfies the common support assumption. See Figure G1 and Table G1 in the Appendix.

Hicks-neutral productivity from output measurement error. In Appendix H, we validate this approach by comparing it with an alternative method that leverages the assumption of invertibility of the investment policy function (8) in Hicks-neutral productivity (Olley and Pakes 1996). The comparison shows that both methods produce closely aligned estimates of $\ddot{\omega}_{jt}^{H}$, providing credible cross-validity for the Kalman filter's use. We prioritize the Kalman filter in our baseline analysis as it does not rely on positive investment values.

Alternative ACF Estimator – As an additional robustness check, Appendix I evaluates an alternative model specification based on the inversion of the investment policy function, that leverages classical estimation methods from Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015). This approach notably allows for interactions between productivity processes, effectively modeling them as a flexible VAR(1). The results are consistent with our baseline findings. However, we favor our baseline estimation approach because it neither depends on positive investment values nor requires the non-parametric estimation of a regression equation with 12 controls.

6. Summary and Concluding Remarks

To conclude, our findings emphasize the factor-biased nature of productivity gains associated with exporting, rather than Hicks-neutral improvements. Focusing on Colombia's export liberalization in the 1980s, we observe that new exporters experience a 4% annual growth in both labor-augmenting and unskilled labor relative productivity, with no changes in Hicks-neutral productivity. These patterns, combined with the complementarity between skilled and unskilled labor and the greater skill intensity among exporters, highlight that exporting promotes technological advancements aimed at reducing unskilled labor reliance. Notably, unskilled labor-augmenting productivity grows by 8% per year, closely tracking increases in machinery assets, while TFP rises by 3% annually.

Our findings shed new light on the impacts of trade liberalization, suggesting that

export-led policies can drive industrialization by promoting unskilled labor-saving technology adoption. Specifically, these policies may encourage manufacturers to adopt advanced technologies from trading partners and invest in automation and machinery that reduce reliance on unskilled labor. However, this shift has critical workforce implications: as unskilled labor relative demand declines, job opportunities for unskilled workers may shrink, while the need for skilled labor rises. These trends underscore the necessity of policies aimed at supporting workforce adaptation to changes in trade and industrialization dynamics.

To better understand the allocation dynamics of skilled and unskilled labor, future research could endogenize wage rates by incorporating their respective supply curves. This extension would allow for a deeper analysis of how changes in manufacturers' skill composition affect equilibrium wage rates and overall welfare. Expanding our production function framework to include labor supply dynamics would facilitate counterfactual simulations, providing insights into the welfare implications of trade liberalization for both skilled and unskilled labor.

Future research could integrate our approach with the literature on trade and quality upgrading (see Verhoogen (2023) for a comprehensive survey), opening promising avenues for exploration. Many existing studies rely on external estimates to calibrate the elasticity of substitution between skilled and unskilled workers—a critical yet difficult-to-estimate parameter. Substitution patterns are central to understanding quality and productivity upgrading, and leveraging partial equilibrium frameworks like ours to estimate these parameters directly could provide greater accuracy. Embedding these estimates into a general equilibrium context would further enhance insights, making this a valuable direction for advancing the field.

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Appendix A. Normalization via Geometric Means

We adopt the normalization approach for the CES production function using geometric means, following de La Grandville (1989), Klump and Preissler (2000), Klump and de La Grandville (2000), de La Grandville and Solow (2006), León-Ledesma, McAdam, and Willman (2010), and Grieco, Li, and Zhang (2016).

This method removes the impact of unit measures on estimation by scaling variables to their respective industry means. It also provides an intuitive interpretation of the normalized share parameters in the CES production function, representing them as the average marginal returns of inputs. Furthermore, it simplifies the estimation process by reducing the determination of share parameters to the estimation of a single unknown parameter.

We define the baseline point, $\bar{Z}$, using the geometric mean of the output and input variables:

$$\bar{X} = \left(\prod_{n=1}^{N} X_n \right)^{\frac{1}{N}}.$$

A.1. Environment

Technology and Productivity Dynamics – From equations (1) and (2), and considering that intermediates, skilled labor, and unskilled labor are static inputs, the selection of the baseline value defines a family of CES functions characterized by the following system of equations:

$$\bar{Q} = \left[\tilde{\alpha}_K \bar{K}^{\rho} + \tilde{\alpha}_M \bar{M}^{\rho} + \tilde{\alpha}_L (\exp(\bar{\omega}^L) \bar{L})^{\rho} \right]^{\frac{1}{\rho}} \exp(\bar{\omega}^H) \tag{A1}$$

$$\bar{L} = \left[\tilde{\alpha}_S \bar{S}^{\theta} + \tilde{\alpha}_U (\exp(\bar{\omega}^R) \bar{U})^{\theta} \right]^{\frac{1}{\theta}} \tag{A2}$$

$$\tilde{\alpha}_K + \tilde{\alpha}_M + \tilde{\alpha}_L = 1 \tag{A3}$$

$$\tilde{\alpha}_S + \tilde{\alpha}_U = 1 \tag{A4}$$

$$\left(\frac{MP_U}{MP_S}\right)_{\bar{Z}} = \frac{\tilde{\alpha}_U(\exp(\bar{\omega}^R)\bar{U})^{\theta}\bar{S}}{\tilde{\alpha}_S\bar{S}^{\theta}\bar{U}} = \bar{\mu}_{US} \tag{A5}$$

$$\left(\frac{MP_L}{MP_M}\right)_{\bar{Z}} = \frac{\tilde{\alpha}_L(\exp(\bar{\omega}^L)\bar{L})^{\rho}\bar{M}}{\tilde{\alpha}_M\bar{M}^{\rho}\bar{L}} = \bar{\mu}_{LM} \tag{A6}$$

$$\left(\frac{MP_M}{MP_K}\right)_{\bar{Z}} = \frac{\tilde{\alpha}_M\bar{M}^{\rho}\bar{K}}{\tilde{\alpha}_K\bar{K}^{\rho}\bar{M}} = \left(\frac{\bar{E}_K}{\tau\bar{E}_M}\right)\bar{\mu}_{MK} \tag{A7}$$

Where $\bar{\omega}^H$, $\bar{\omega}^L$, and $\bar{\omega}^R$ represent the productivities associated with the "average" plant producing $\bar{Q}$ using $\bar{K}$, $\bar{M}$, $\bar{S}$, and $\bar{U}$ respectively, and $\bar{\mu}_{US}$, $\bar{\mu}_{LM}$, and $\bar{\mu}_{MK}$ denote the average optimal static marginal rates of substitution between unskilled and skilled labor, the labor aggregate and intermediates, and intermediates and capital respectively.

Then, the marginal rates of substitution correspond to the relative prices $\frac{\bar{W}^U}{\bar{W}^S}$, $\frac{\bar{P}^L}{\bar{P}^M}$, and $\frac{\bar{P}^M}{\bar{P}^K}$, where $\bar{W}^S$ and $\bar{W}^U$ are the geometric mean wage rates for skilled and unskilled workers, and $\bar{P}^M$, $\bar{P}^L$, and $\bar{P}^K$ are the geometric mean price indexes for materials, the CES aggregate of skilled and unskilled labor, and capital.

Since equations (A6), (A7), and (A5) derive from cost minimization, the parameter τ measures the mean deviation of capital stock from its statically optimal level and accounts for the dynamic nature of the capital allocation problem, as in our case (for a more detailed treatment, see Online Appendix 4 in Grieco, Li, and Zhang (2016)). Finally, $\bar{E}_M$ and $\bar{E}_K$ represent the geometric average expenditures on materials and capital, respectively.

Equations (A3), (A4), (A6), (A7), and (A5) define a system of five equations in five unknown CES parameters. Solving this system yields the following parameters:

$$\tilde{\alpha}_U = \frac{\frac{\bar{E}_U}{(\exp(\bar{\omega}_R)\bar{U})^{\theta}}}{\frac{\bar{E}_U}{(\exp(\bar{\omega}_R)\bar{U})^{\theta}} + \frac{\bar{E}_S}{\bar{S}^{\theta}}} \tag{A8}$$

$$\tilde{\alpha}_S = 1 - \tilde{\alpha}_U \tag{A9}$$

$$\tilde{\alpha}_M = \frac{\frac{\bar{E}_M}{\bar{M}^{\rho}}}{\frac{\bar{E}_M}{\bar{M}^{\rho}} + \frac{\bar{E}_L}{(\exp(\bar{\omega}_L)\bar{L})^{\rho}} + \frac{\tau\bar{E}_M}{\bar{K}^{\rho}}} \tag{A10}$$

(A11) $$\tilde{\alpha}_L = \frac{\frac{\bar{E}_L}{(\exp(\bar{\omega}_L)\bar{L})^\rho}}{\frac{\bar{E}_M}{\bar{M}^\rho} + \frac{\bar{E}_L}{(\exp(\bar{\omega}_L)\bar{L})^\rho} + \frac{\tau\bar{E}_M}{\bar{K}^\rho}}$$

(A12) $$\tilde{\alpha}_K = 1 - \tilde{\alpha}_M - \tilde{\alpha}_L$$

Then, the following normalization of the production function results from re-parametrization:

(A13) $$Q_{jt} = \bar{Q}\left[\alpha_K\left(\frac{K_{jt}}{\bar{K}}\right)^\rho + \alpha_M\left(\frac{M_{jt}}{\bar{M}}\right)^\rho + \alpha_L\left(\exp(\ddot{\omega}^L_{jt})\frac{L_{jt}}{\bar{L}}\right)^\rho\right]^{\frac{1}{\rho}}\exp(\ddot{\omega}^H_{jt})$$

Where

(A14) $$\frac{L_{jt}}{\bar{L}} = \left[\alpha_S\left(\frac{S_{jt}}{\bar{S}}\right)^\theta + \alpha_U\left(\exp(\ddot{\omega}^R_{jt})\frac{U_{jt}}{\bar{U}}\right)^\theta\right]^{\frac{1}{\theta}}$$

(A15) $$\ddot{\omega}^X_{jt} = \omega^X_{jt} - \bar{\omega}^X \quad \forall X \in \{H, L, R\}$$

and

(A16) $$\alpha_S = \frac{\bar{E}_S}{\bar{E}_S + \bar{E}_U}$$

(A17) $$\alpha_U = 1 - \alpha_S$$

(A18) $$\alpha_M = \frac{\bar{E}_M}{\bar{E}_M + \bar{E}_L + \tau\bar{E}_M}$$

(A19) $$\alpha_L = \frac{\bar{E}_L}{\bar{E}_M + \bar{E}_L + \tau\bar{E}_M}$$

(A20) $$\alpha_K = \frac{\tau\bar{E}_M}{\bar{E}_M + \bar{E}_L + \tau\bar{E}_M}$$

$\bar{E}_S$ and $\bar{E}_U$ represent the geometric average expenditures on skilled and unskilled labor, respectively. $\bar{E}_L$ represents the geometric average expenditures on the labor composite. In this normalization, each parameter α_X corresponds to the marginal return of input X (expressed in normalized units) for a firm with inputs, productivity, and input prices set at

their geometric mean levels.

Since $\ddot{\omega}_{jt}^{H}$, $\ddot{\omega}_{jt}^{L}$, and $\ddot{\omega}_{jt}^{R}$ are obtained by subtracting a constant term from the Markov processes governing ω_{jt}^{H}, ω_{jt}^{L}, and ω_{jt}^{R}, respectively, it follows that $\ddot{\omega}_{jt}^{H}$, $\ddot{\omega}_{jt}^{L}$, and $\ddot{\omega}_{jt}^{R}$ also follow the same Markov process. These can be expressed as: $\forall X \in (H, L, R)$,

$$\ddot{\omega}_{jt}^{X} = \ddot{\iota}_{t} + \ddot{\iota}_{s} + \rho_{X}\ddot{\omega}_{jt-1}^{X} + \beta_{X}^{e} e_{jt-1} + \beta_{X}^{i} i_{jt-1} + \beta_{X}^{ei}\left(e_{jt-1} \cdot i_{jt-1}\right) + \xi_{jt}^{X} \tag{A21}$$

A.2. Static Input Allocation Problem

Let $\ddot{X}_{jt}$ represent a normalized variable, defined as $\ddot{X}_{jt} = \frac{X_{jt}}{\bar{X}}$, where $\bar{X} = \left(\prod_{n=1}^{N} X_{n}\right)^{\frac{1}{N}}$. Plant j solves the following normalized cost minimization problem to determine the optimal quantities of variable inputs:

$$\begin{aligned}
&\min_{S_{jt}, U_{jt}, M_{jt}} \quad W_{jt}^{S} S_{jt} + W_{jt}^{U} U_{jt} + P_{jt}^{M} M_{jt} \\
&\text{s.t.} \quad E_{t}[Q_{jt}] \geq (1 - e_{jt}) Q^{D} + e_{jt} Q^{X} \\
&Q_{jt} = \bar{Q}\left[\alpha_{K}\ddot{K}_{jt}^{\rho} + \alpha_{M}\ddot{M}_{jt}^{\rho} + \alpha_{L}(\exp(\ddot{\omega}_{jt}^{L})\ddot{L}_{jt})^{\rho}\right]^{\frac{1}{\rho}} \exp(\ddot{\omega}_{jt}^{H}) \\
&\ddot{L}_{jt} = \left[\alpha_{S}\ddot{S}_{jt}^{\theta} + \alpha_{U}\left(\exp(\ddot{\omega}_{jt}^{R})\ddot{U}_{jt}\right)^{\theta}\right]^{\frac{1}{\theta}}
\end{aligned} \tag{A22}$$

A.3. Dynamic Export and Investment Decisions

Investment Policy Function – Let $\ddot{\Omega}_{jt}$ denote the vector of normalized state variables, except for e_{jt}:

$$\ddot{\Omega}_{jt} \equiv (\ddot{K}_{jt}, W_{jt}^{S}, W_{jt}^{U}, P_{jt}^{M}, \exp(\ddot{\omega}_{jt}^{H}), \exp(\ddot{\omega}_{jt}^{L}), \exp(\ddot{\omega}_{jt}^{R})) \tag{A23}$$

Let $\pi(\ddot{\Omega}_{jt}, e_{jt})$ be the normalized profit function. Given the state variable $(\ddot{\Omega}_{jt}, e_{jt})$, equations (6) and (7) imply that the normalized investment decision reads:

$$\ddot{I}_{jt} = \ddot{\imath}(\ddot{\Omega}_{jt}, e_{jt}, e_{jt+1}) \tag{A24}$$

Again, we assume that the normalized investment policy function, conditional on the other state variables, is strictly monotonic in (normalized) Hicks-neutral productivity, $\exp(\ddot{\omega}^{H}_{jt})$.

Conditional Choice Probability of Exporting – Based on Equation (6), we can characterize plant j's conditional choice probability of exporting in period $t + 1$, given the normalized state variables $(\ddot{\Omega}_{jt}, e_{jt})$, as

$$Pr(e_{jt+1} = 1|\ddot{\Omega}_{jt}, e_{jt}) = \int_{\gamma_{jt}} \mathbb{1}\left\{EV^{1}(\ddot{\Omega}_{jt}, e_{jt}) - EV^{0}(\ddot{\Omega}_{jt}, e_{jt}) \geq \gamma_{jt}\right\} \mathrm{d}G(\gamma_{jt}|e_{jt}). \tag{A25}$$

End of Period – Given that the measurement error ε_{jt} has a zero mean, the geometric mean of observed output, $\tilde{Q}_{jt}$, is equal to the geometric mean of the planned output, Q_{jt}, denoted as $\bar{Q}$.

Appendix B. Kalman Procedures

This appendix details the Kalman filtering procedure used to compute the likelihood function for the state-space model in equations (23) and (24). Recall that the state-space representation of the estimating equation in Step 3 is:

$$\log \ddot{\tilde{Q}}_{jt} = H\pi_{jt} + AY_{jt} + \ddot{\iota}_t + \ddot{\iota}_s, \tag{A26}$$

$$\pi_{jt} = F\pi_{jt-1} + Gu_{jt}. \tag{A27}$$

For each plant j, the Kalman filtering steps proceed as follows (Hamilton (1994a)):

$$\begin{aligned}
&\pi_{j,0|0} = \mathbb{E}(\pi_{j0}) = \vec{0}_{3\times 1},\\
&P_{j,0|0} = \mathbb{E}(\pi_{j,0|0}\pi'_{j,0|0}),\\
&\pi_{j,t+1|t} = F\pi_{j,t|t},\\
&P_{j,t+1|t} = FP_{j,t|t}F' + G\Sigma G',\\
&\nu_{jt+1} = \log \ddot{\tilde{Q}}_{jt+1} - H\pi_{j,t+1|t} - AY_{jt} - \ddot{\iota}_{t+1} - \ddot{\iota}_s,\\
&N_{j,t+1} = HP_{j,t+1|t}H',\\
&O_{j,t+1} = P_{j,t+1|t}H'N^{-1}_{j,t+1},\\
&\pi_{j,t+1|t+1} = \pi_{j,t+1|t} - O_{j,t+1}\nu_{jt+1},\\
&P_{j,t+1|t+1} = (I - O_{j,t+1}H)P_{j,t+1|t}.
\end{aligned}$$

At each iteration, we compute the log-likelihood of observing $\log \ddot{\tilde{Q}}_{jt+1}$ using ν_{jt+1} and $N_{j,t+1}$:

$$\log f(\log \ddot{\tilde{Q}}_{jt+1}|I_t) = -\log(\det(N_{j,t+1})) - \nu'_{jt+1}N^{-1}_{j,t+1}\nu_{jt+1}.$$

The contribution of plant j to the overall likelihood is then:

$$L_j((\sigma_H^2, \sigma_\varepsilon^2)|D) = -\sum_{t=0}^{T_j} \log\left(\det(N_{j,t})\right) - \sum_{t=0}^{T_j} \nu_{jt}' N_{j,t}^{-1} \nu_{jt},$$

and the total likelihood function is

$$\mathcal{L}((\sigma_H^2, \sigma_\varepsilon^2)|D) = \sum_{j=1}^{J} L_j((\sigma_H^2, \sigma_\varepsilon^2)|D).$$

Upon estimating $(\sigma_H^2, \sigma_\varepsilon^2)$ via MLE, we recover the estimates of ξ_{jt}^H and ε_{jt} using the Kalman smoother (Hamilton 1994b), based on all available information over the sample period. This retrospective improvement yields more precise estimates of π_{jt}, denoted by $\pi_{j,t|T_j}$. Specifically, given the Kalman-filtered variables $(\pi_{j,t|t}, P_{j,t+1|t+1}, \pi_{j,t|t+1}, P_{j,t+1|t})$, we recursively apply the Kalman smoother from T_j back to $t = 1$:

$$\begin{aligned}
&\widehat{\pi}_{j,T_j|T_j} = \pi_{j,T_j|T_j},\\
&\widehat{P}_{j,T_j|T_j} = P_{j,T_j|T_j},\\
&C_{jt} = P_{j,t|t} F' P_{j,t+1|t}^{-1},\\
&\widehat{\pi}_{j,t|T_j} = \pi_{j,t|t} + C_{jt}(\widehat{\pi}_{j,t+1|T_j} - \pi_{j,t+1|t}),\\
&\widehat{P}_{j,t|T_j} = P_{j,t|t} + C_{jt}(\widehat{P}_{j,t+1|T_j} - P_{j,t+1|t}) C_{jt}'.
\end{aligned}$$

The estimates $\hat{\xi}_{jt}^H$ and $\hat{\varepsilon}_{jt}$ correspond to the first and second elements of $\widehat{\pi}_{j,t|T_j}$, respectively. Finally, we measure $\ddot{\omega}_{jt}^H$ as follows:

$$\ddot{\omega}_{jt}^H = \log \ddot{\tilde{Q}}_{jt} - \hat{\varepsilon}_{jt} - \frac{1}{\hat{\rho}} \log\left[\hat{\alpha}_K \ddot{K}_{jt}^{\hat{\rho}} + \hat{\alpha}_M \ddot{M}_{jt}^{\hat{\rho}} + \hat{\alpha}_L \ddot{L}_{jt}^{\hat{\rho}}\right].$$

Appendix C. Propensity Score Matching: Supplementary Figures

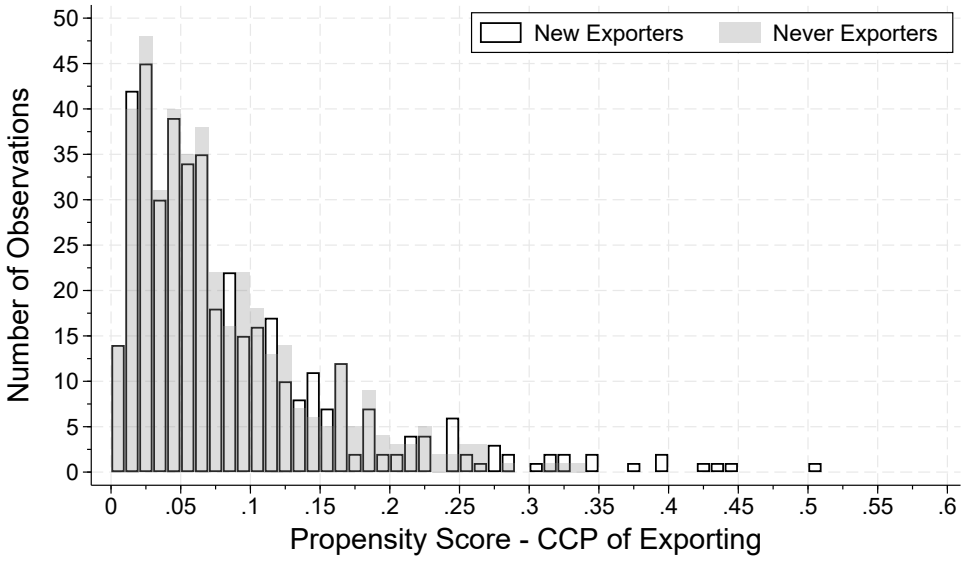


FIGURE C1. PSM Common Support: New Exporters vs Never Exporters

This figure presents histograms of estimated propensity scores (CCP of exporting) for new exporters one year prior to exporting and for their second nearest neighboring control plants. Clear bars show the frequency of new exporter observations, while shaded bars represent the frequency of matched never-exporter observations.

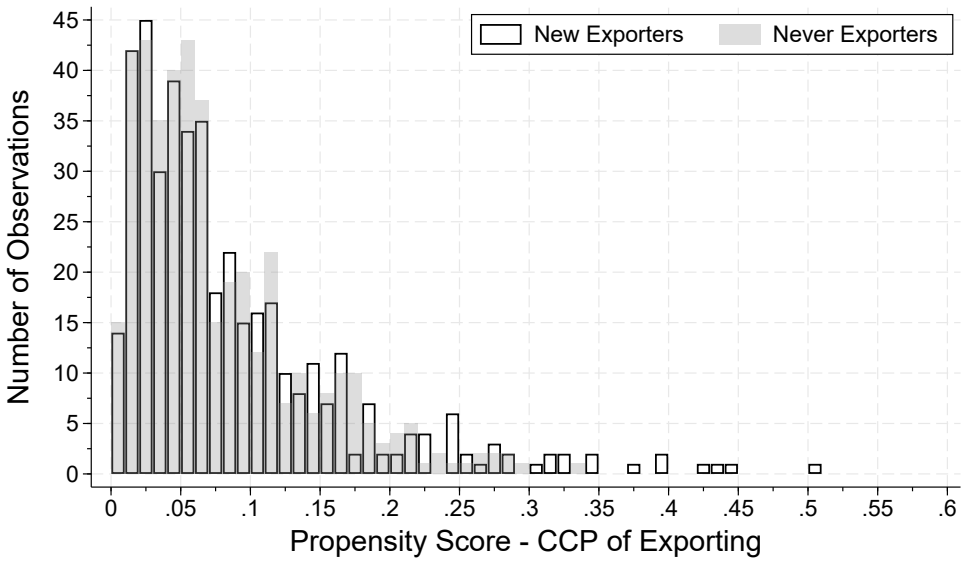


FIGURE C2. PSM Common Support: New Exporters vs Never Exporters

This figure presents histograms of estimated propensity scores (CCP of exporting) for new exporters one year prior to exporting and for their third nearest neighboring control plants. Clear bars show the frequency of new exporter observations, while shaded bars represent the frequency of matched never-exporter observations.

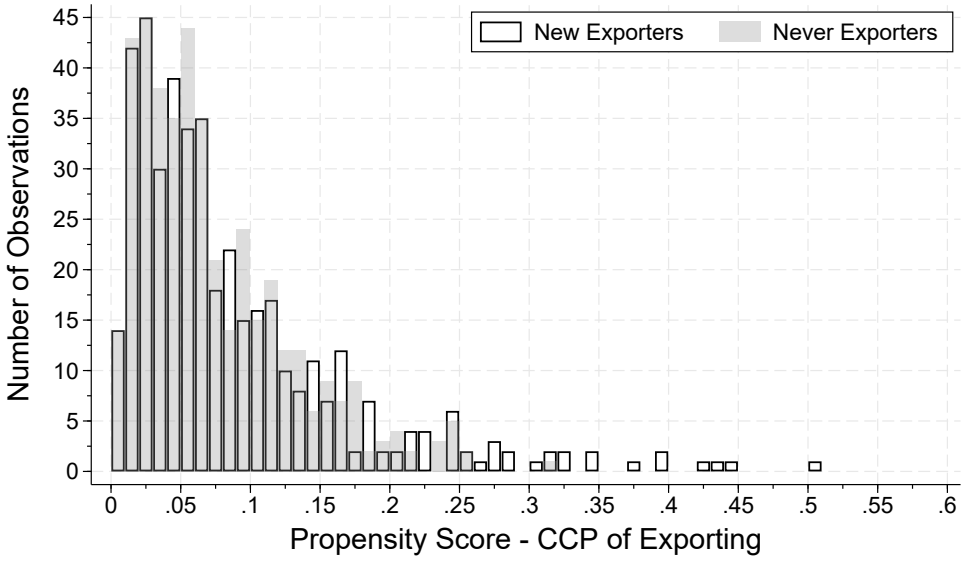


FIGURE C3. PSM Common Support: New Exporters vs Never Exporters

This figure presents histograms of estimated propensity scores (CCP of exporting) for new exporters one year prior to exporting and for their fourth nearest neighboring control plants. Clear bars show the frequency of new exporter observations, while shaded bars represent the frequency of matched never-exporter observations.

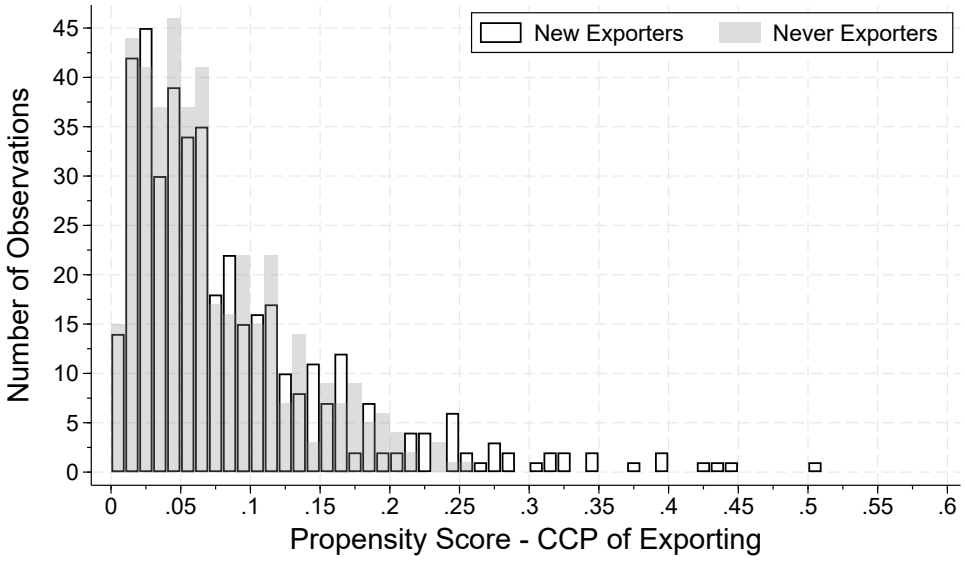


FIGURE C4. PSM Common Support: New Exporters vs Never Exporters

This figure presents histograms of estimated propensity scores (CCP of exporting) for new exporters one year prior to exporting and for their fifth nearest neighboring control plants. Clear bars show the frequency of new exporter observations, while shaded bars represent the frequency of matched never-exporter observations.

Appendix D. Effects of Exporting: Supplementary Figures

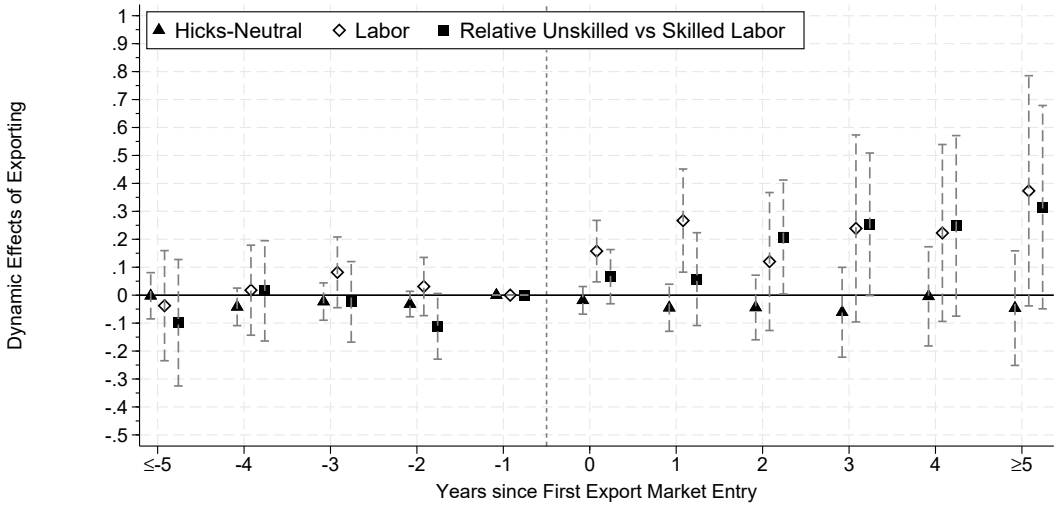


FIGURE D1. Estimated Local Effects of Exporting

This figure displays the estimated effects of exporting on Hicks-neutral productivity, labor-augmenting productivity, and unskilled labor relative productivity, each with 90% non-parametrically bootstrapped confidence intervals.

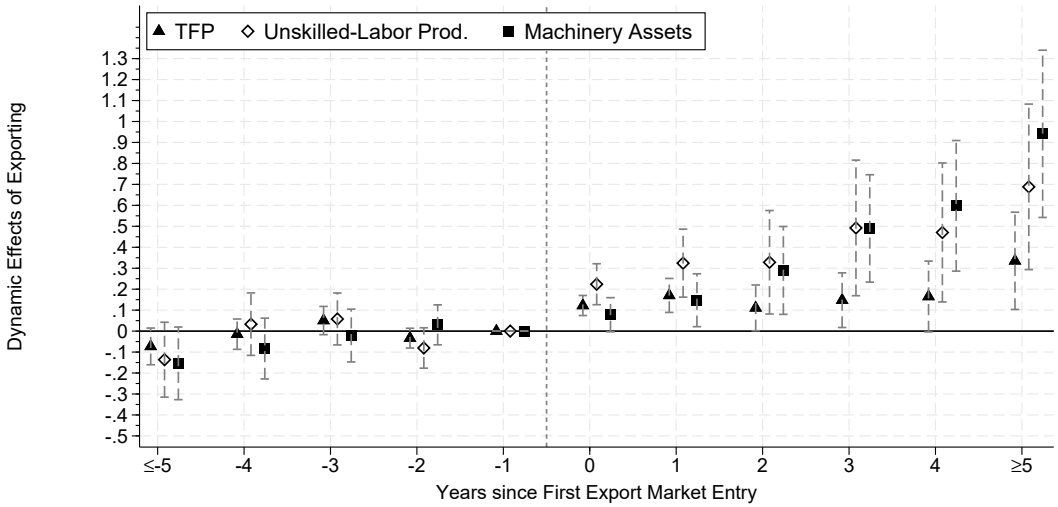


FIGURE D2. Estimated Local Effects of Exporting

This figure displays the local effects of exporting on TFP, unskilled labor-augmenting productivity, and the stock of machinery equipment, along with 90% non-parametrically bootstrapped confidence intervals.

Appendix E. Colombia Administrative Departments



FIGURE E1. Map of Colombia's Administrative Departments

Sourced from Wikipedia.
By Milenioscuro - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=44931327.

Appendix F. Instruments Construction

(i) $\Delta \log \left(\frac{\ddot{W}^U_{jt-1}}{\ddot{W}^S_{jt-1}} \right) := \log \left(\frac{\ddot{W}^U_{jt-1}}{\ddot{W}^S_{jt-1}} \right) - \log \left(\frac{\ddot{W}^U_{jt-2}}{\ddot{W}^S_{jt-2}} \right)$.

(ii) $\Delta \log \ddot{W}^S_{jt-1} := \log \ddot{W}^S_{jt-1} - \log \ddot{W}^S_{jt-2}$.

(iii) Let $s(j)$ denote the industry and $r(j)$ the administrative geographical department of plant j. The instrument is constructed as the lagged weighted average of log relative wages of plants operating in the same industry and department as plant j, excluding plant j itself:

$$\sum_{\substack{i \neq j, \\ i \in r \cdot s(j)}} w_{it-1} \log \left(\frac{\ddot{W}^U_{it-1}}{\ddot{W}^S_{it-1}} \right)$$

where the weight w_{it-1} is given by

$$w_{it-1} := \frac{Q_{it-1}}{\sum\limits_{\substack{i \neq j, \\ i \in r \cdot s(j)}} Q_{it-1}}$$

and represents the share of output produced by plant i relative to the total output in the department-industry, $r \cdot s(j)$, excluding plant j.

(iv) Let $s(j)$ denote the industry and $r(j)$ the administrative geographical department of plant j. Let $a(r)$ be the set of administrative departments adjacent to $r(j)$. The instrument is constructed as the lagged weighted average of log relative wages of plants operating in the same industry and in adjacent geographical departments as plant j:

$$\sum_{\substack{i \in a(r(j)), \\ i \in s(j)}} w_{it-1} \log \left(\frac{\ddot{W}^U_{it-1}}{\ddot{W}^S_{it-1}} \right)$$

where the weight w_{it-1} is given by

$$w_{it-1} := \frac{Q_{it-1}}{\sum\limits_{\substack{i \in a(r(j)),\\ i \in s(j)}} Q_{it-1}}$$

and represents the share of output produced by plant i relative to the total output in the same industry from departments adjacent to $r(j)$.

(v) Let $g_{st}\left(\frac{\ddot{S}_{st}}{\ddot{U}_{st}}\right)$ denote the national annual growth rate at time t and in industry $s(j)$ of the ratio between the (normalized) skilled and unskilled workforce:

$$g_{st}\left(\frac{\ddot{S}_{st}}{\ddot{U}_{st}}\right) := \frac{1}{4}\left[\log\left(\frac{\sum\limits_{i \in s(j)} \ddot{S}_{it}}{\sum\limits_{i \in s(j)} \ddot{U}_{it}}\right) - \log\left(\frac{\sum\limits_{i \in s(j)} \ddot{S}_{it-4}}{\sum\limits_{i \in s(j)} \ddot{U}_{it-4}}\right)\right].$$

Let $s_{rs,t-4}$ represent the lagged relative ratio between the (normalized) skilled and unskilled workforce at the industry-department level relative to the same ratio at the department level:

$$s_{rs,t-4} := \frac{\sum\limits_{i \in r \cdot s(j)} \ddot{S}_{it-4}}{\sum\limits_{i \in r \cdot s(j)} \ddot{U}_{it-4}} \Bigg/ \frac{\sum\limits_{i \in r(j)} \ddot{S}_{it-4}}{\sum\limits_{i \in r(j)} \ddot{U}_{it-4}}.$$

The instrument is constructed as the sum across industries of the interaction between the growth rate and the regional share:

$$\sum_{s} s_{rs,t-4} g_{st}\left(\frac{\ddot{S}_{st}}{\ddot{U}_{st}}\right).$$

(vi) Let the predicted relative ratio between the (normalized) skilled and unskilled workforce at the industry-department level relative to the same ratio at the department level

be defined as:

$$\hat{s}_{rs,t} := s_{rs,t-4} g_{st} \left(\frac{\ddot{S}_{st}}{\ddot{U}_{st}} \right).$$

Let the national industry wage premia be the fitted values from a regression, performed separately for each year, of the relative wage on industry fixed effects:

$$\frac{\ddot{W}^U_{jt}}{\ddot{W}^S_{jt}} = i_s + resid_{jt}.$$

Finally, the instrument is constructed as the sum across industries of the interaction between the national industry wage premia and the difference between the predicted and the lagged relative ratio of (normalized) skilled to unskilled workforce at the industry-department level relative to the same ratio at the department level:

$$\sum_s \nu_{st} (\hat{s}_{rs,t} - s_{rs,t-4}).$$

Appendix G. Unfiltered Hicks-Neutral Productivity

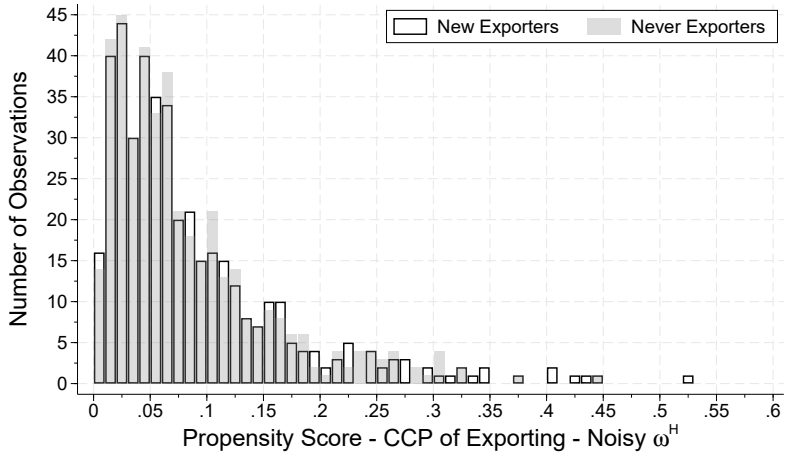


FIGURE G1. PSM Common Support: New Exporters vs Never Exporters - Unfiltered $\ddot{\omega}^H$

This figure presents histograms of estimated propensity scores for new exporters and for their nearest neighboring control plants. The propensity score matching algorithm is implemented using the unfiltered estimates of $\ddot{\omega}^H$.

TABLE G1. Matching Balancedness: New Exporters vs Never Exporters - Unfiltered $\ddot{\omega}^H$

	T	C	Difference	t stat	p value
$\log \ddot{K}_{jt-1}$	0.621	0.463	0.157	1.250	0.21
$\log \ddot{W}^S_{jt-1}$	0.150	0.116	0.034	0.97	0.33
$\log \ddot{W}^U_{jt-1}$	0.028	0.014	0.014	0.53	0.59
$\log \ddot{P}^M_{jt-1}$	-0.045	-0.045	0.000	0.00	1.00
$\ddot{\omega}^H_{jt-1} + \varepsilon_{jt-1}$	0.099	0.164	-0.065	-0.79	0.43
$\ddot{\omega}^S_{jt-1}$	0.491	0.428	0.063	0.45	0.65
$\ddot{\omega}^R_{jt-1}$	0.306	0.170	0.136	0.98	0.33
Obs.	424	1,833			

NOTE.– This table presents the summary statistics of the matched sample: the first two columns display the matched groups sample averages; the last three columns show the difference in means between the two groups, along with the corresponding *t*-statistic and *p*-value.

Appendix H. Cross-Validation for Kalman Filter

In this appendix, we validate the use of the Kalman filter to extract $\ddot{\omega}_{jt}^{H}$ from the noisy estimates $\widehat{\ddot{\omega}_{jt}^{H} + \varepsilon_{jt}}$. As an alternative to the Kalman filter, we assume that the normalized investment policy function (A24) is strictly monotonic in $\exp(\ddot{\omega}_{jt}^{H})$, conditional on the other state variables (Olley and Pakes 1996).

By inverting the investment policy function, we derive the linear projection:

$$\widehat{\ddot{\omega}_{jt}^{H} + \varepsilon_{jt}} = \ddot{\omega}^{H}\left(\log \ddot{I}_{jt}, \ddot{\omega}_{jt}^{L}, \ddot{\omega}_{jt}^{R}, \log \ddot{K}_{jt}, \log W_{jt}^{S}, \log W_{jt}^{U}, \log P_{jt}^{M}, e_{jt}, e_{jt+1}\right) + \varepsilon_{jt}. \tag{A28}$$

We estimate (A28) using third-degree polynomials of all variables and their interactions, with year and industry dummies included. To address high-dimensionality and multicollinearity, we apply LASSO for sparse approximation. The resulting fitted value, $\tilde{\ddot{\omega}}_{jt}^{H}$, provides an alternative measure of $\ddot{\omega}_{jt}^{H}$.

Figure H1 presents a scatter plot comparing Kalman-filtered estimates, $\ddot{\omega}_{jt}^{H}$, with investment-based predictions, $\tilde{\ddot{\omega}}_{jt}^{H}$. The data points form a concentrated cluster along the 45-degree line, indicating strong agreement between the two methods. This alignment underscores the robustness of the Kalman filter.

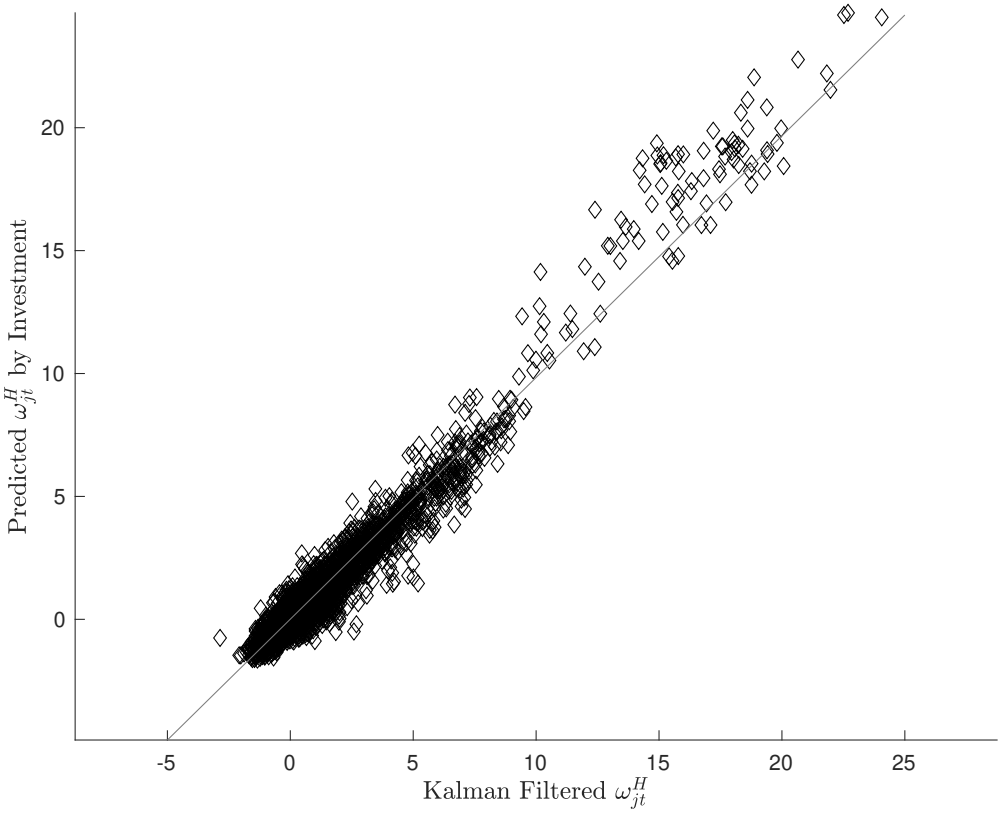


FIGURE H1. Comparison of Estimated ω_{jt}^H: Kalman-Filtered vs. Investment-base Prediction

Figure H1 presents a scatter plot comparing Kalman-filtered estimates, $\ddot{\omega}_{jt}^H$, with investment-based predictions, $\tilde{\ddot{\omega}}_{jt}^H$. The data points form a concentrated cluster along the 45-degree line, indicating strong agreement between the two methods.

Appendix I. Alternative ACF Specification

In this appendix, we consider the following version of our baseline specification:

$$\ddot{Q}_{jt} = \left[\alpha_K \left(\exp(\ddot{\omega}^K_{jt})\ddot{K}_{jt}\right)^{\rho} + \alpha_M \left(\exp(\ddot{\omega}^M_{jt})\ddot{M}_{jt}\right)^{\rho} + \alpha_L \left(\ddot{L}_{jt}\right)^{\rho}\right]^{\frac{1}{\rho}}, \tag{A29}$$

where

$$\ddot{L}_{jt} = \left[\alpha_S \left(\exp(\ddot{\omega}^S_{jt})\ddot{S}_{jt}\right)^{\theta} + \alpha_U \left(\exp(\ddot{\omega}^U_{jt})\ddot{U}_{jt}\right)^{\theta}\right]^{\frac{1}{\theta}}. \tag{A30}$$

We assume that the material- and capital-augmenting efficiencies evolve according to the same law of motion:

$$\ddot{\omega}^K_{jt} = \ddot{\omega}^M_{jt}, \tag{A31}$$

and the three efficiencies follow a controlled VAR(1) process:

$$\begin{bmatrix} \ddot{\omega}^K_{jt+1} \\ \ddot{\omega}^S_{jt+1} \\ \ddot{\omega}^U_{jt+1} \end{bmatrix} = \begin{bmatrix} \rho_{KK} & \rho_{KS} & \rho_{KU} \\ \rho_{SK} & \rho_{SS} & \rho_{SU} \\ \rho_{UK} & \rho_{US} & \rho_{UU} \end{bmatrix} \begin{bmatrix} \ddot{\omega}^K_{jt} \\ \ddot{\omega}^S_{jt} \\ \ddot{\omega}^U_{jt} \end{bmatrix} + \begin{bmatrix} \beta^e_K & \beta^i_K & \beta^{ei}_K \\ \beta^e_S & \beta^i_U & \beta^{ei}_U \\ \beta^e_U & \beta^i_S & \beta^{ei}_S \end{bmatrix} \begin{bmatrix} e_{jt-1} \\ i_{jt-1} \\ e_{jt-1}i_{jt-1} \end{bmatrix} + \begin{bmatrix} \xi^K_{jt+1} \\ \xi^S_{jt+1} \\ \xi^U_{jt+1} \end{bmatrix}. \tag{A32}$$

Following Zhang (2019), we reformulate the production function (A29) in terms of relative efficiencies:

$$\ddot{Q}_{jt} = \exp(\ddot{\omega}^K_{jt}) \left[\alpha_K \left(\ddot{K}_{jt}\right)^{\rho} + \alpha_M \left(\ddot{M}_{jt}\right)^{\rho} + \alpha_L \left(\exp(\ddot{\omega}^L_{jt})\mathcal{L}_{jt}\right)^{\rho}\right]^{\frac{1}{\rho}}, \tag{A33}$$

with

$$\mathcal{L}_{jt} = \left[\alpha_S \left(\ddot{S}_{jt}\right)^{\theta} + \alpha_U \left(\exp(\ddot{\omega}^{UR}_{jt})\ddot{U}_{jt}\right)^{\theta}\right]^{\frac{1}{\theta}}, \tag{A34}$$

where

$$\ddot{\omega}_{jt}^{L} = \ddot{\omega}_{jt}^{S} - \ddot{\omega}_{jt}^{K}, \tag{A35}$$

$$\ddot{\omega}_{jt}^{UR} = \ddot{\omega}_{jt}^{U} - \ddot{\omega}_{jt}^{S}. \tag{A36}$$

Exploiting the first-order conditions of the short-run cost minimization problem, we derive closed forms for $\ddot{\omega}_{jt}^{UR}$ and $\ddot{\omega}_{jt}^{L}$:

$$\ddot{\omega}_{jt}^{UR} = \frac{1}{\theta}\left[\log\frac{E_{jt}^{U}}{E_{jt}^{S}} + \log\frac{\alpha_S}{\alpha_U}\right] + \log\frac{\ddot{S}_{jt}}{\ddot{U}_{jt}}, \tag{A37}$$

$$\ddot{\omega}_{jt}^{L} = \frac{1}{\rho}\left[\log\frac{E_{jt}^{L}}{E_{jt}^{M}} + \log\frac{\alpha_M}{\alpha_L}\right] + \log\frac{\mathcal{L}_{jt}}{\ddot{M}_{jt}}, \tag{A38}$$

with a closed form of $\mathcal{L}_{jt}$:

$$\mathcal{L}_{jt} = \ddot{S}_{jt}\alpha_S^{\frac{1}{\theta}}\left(\frac{E_{jt}^{S} + E_{jt}^{U}}{E_{jt}^{S}}\right)^{\frac{1}{\theta}}. \tag{A39}$$

Plugging these expressions into the production function (A33) and taking the logarithm, we obtain

$$\log\tilde{Q}_{jt} = \frac{1}{\rho}\log\left[\alpha_K(\ddot{K}_{jt})^{\rho} + \alpha_M(\ddot{M}_{jt})^{\rho}\left(1 + \frac{E_{jt}^{L}}{E_{jt}^{M}}\right)\right] + \ddot{\omega}_{jt}^{K} + \varepsilon_{jt}. \tag{A40}$$

Estimating equation (A40) requires addressing a scalar unobservable, $\ddot{\omega}_{jt}^{K}$, which is a standard situation treated by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015). We assume that the normalized investment policy function (8) is strictly monotonic in $\exp(\ddot{\omega}_{jt}^{K})$, conditional on all other normalized state variables.

We replace $\ddot{\omega}_{jt}^{K}$ with the inverse function of the investment policy and substitute

$\ddot{\omega}^S_{jt}$, $\ddot{\omega}^U_{jt}$ using the characterizations (A37) and (A38). This yields the following first-stage regression equation:

$$\log \tilde{Q}_{jt} = y\Bigg(\log \ddot{I}_{jt}, \log \frac{E^S_{jt}}{E^U_{jt}}, \log \frac{\ddot{S}_{jt}}{\ddot{U}_{jt}}, \log \frac{E^L_{jt}}{E^M_{jt}}, \log \frac{\ddot{S}_{jt}}{\ddot{M}_{jt}}, \log \ddot{K}_{jt}, \log \ddot{M}_{jt}, \log W^S_{jt}, \log W^U_{jt}, \log P^M_{jt}, e_{jt}, e_{jt+1} \Bigg) + \varepsilon_{jt}. \tag{A41}$$

We estimate this equation using a complete set of third-degree polynomials in all variables and their interactions, along with a full set of year and industry dummies. To address potential high dimensionality and multicollinearity, we apply sparse approximation methods, specifically LASSO. In this stage, we identify the predicted output $\hat{\phi}_{jt}$ and measurement error $\hat{\varepsilon}_{jt}$.

In the second stage, we recover $\Theta = (\rho, \theta)$ that best satisfies the constrained generalized method of moments (GMM) conditions:

$$\mathbf{m}(\Theta) \equiv \mathbb{E}\left(\begin{bmatrix} \xi^K_{jt}(\Theta) \times Z^H_{jt} \\ \xi^S_{jt}(\Theta) \times Z^S_{jt} \\ \xi^U_{jt}(\Theta) \times Z^U_{jt} \end{bmatrix} \right) = 0, \tag{A42}$$

where $(\xi^K_{jt}(\Theta), \xi^S_{jt}(\Theta), \xi^U_{jt}(\Theta))$ are obtained by regressing $(\omega^K_{jt}, \omega^S_{jt}, \omega^U_{jt})$ on $(\omega^K_{jt}, \omega^S_{jt}, \omega^U_{jt}, e_{jt-1}, i_{jt-1}, e_{jt-1}i_{jt-1})$, and

$$\omega^K_{jt}(\Theta) = \hat{\phi}_{jt} - \frac{1}{\rho} \log \left[\alpha_K (\ddot{K}_{jt})^\rho + \alpha_M (\ddot{M}_{jt})^\rho \left(1 + \frac{E^L_{jt}}{E^M_{jt}} \right) \right],$$

$$\omega^S_{jt}(\Theta) = \frac{1}{\rho} \left[\log \frac{E^L_{jt}}{E^M_{jt}} + \log \frac{\alpha_M}{\alpha_L} \right] + \log \frac{\mathcal{L}_{jt}}{\ddot{M}_{jt}} + \omega^K_{jt}(\Theta),$$

$$\omega^S_{jt}(\Theta) = \frac{1}{\theta} \left[\log \frac{E^U_{jt}}{E^S_{jt}} + \log \frac{\alpha_S}{\alpha_U} \right] + \log \frac{\ddot{S}_{jt}}{\ddot{U}_{jt}} + \omega^S_{jt}(\Theta),$$

with the following constraints on the distributional parameters[30]:

$$\alpha_S = \frac{\bar{E}_S}{\bar{E}_S + \bar{E}_U}, \tag{A43}$$

$$\alpha_U = 1 - \alpha_S, \tag{A44}$$

$$\alpha_M = \frac{\bar{E}_M}{\bar{E}_M + \bar{E}_L + \bar{E}_K}, \tag{A45}$$

$$\alpha_L = \frac{\bar{E}_L}{\bar{E}_M + \bar{E}_L + \bar{E}_K}, \tag{A46}$$

$$\alpha_K = 1 - \alpha_M - \alpha_L. \tag{A47}$$

In practice, we employ the following instruments:

$$\begin{aligned}
Z_{jt}^K &= \left(\log \ddot{K}_{jt-1}, \log \ddot{S}_{jt-1}, \log \ddot{U}_{jt-1}, \log \ddot{M}_{jt-1}\right)', \\
Z_{jt}^S &= \left(\log\left(\frac{\ddot{E}_{jt-1}^S}{\ddot{E}_{jt-1}^M}\right)\right)', \\
Z_{jt}^U &= \left(\log\left(\frac{\ddot{B}_{jt-1}^S}{\ddot{B}_{jt-1}^U}\right), \log\left(\frac{\ddot{S}_{jt-1}}{\ddot{U}_{jt-1}}\right)\right)'.
\end{aligned}$$

Table I1 reports the production function estimates based on the alternative specification. The results yield an estimate of θ that closely aligns with the baseline specification, reconfirming the complementarity between skilled and unskilled workers in the manufacturing process. Furthermore, the ACF-style approach to extracting output measurement errors produces a similarly dispersed ε_{jt}, with a standard deviation of 0.257.

Table I2 reports the estimates for the VAR(1) process. Although this specification is not directly comparable to our baseline estimates, the results reinforce our main conclusion regarding unskilled labor-saving technological progress driven by exporting. Specifically,

[30] Note that we approximate capital expenditure using its user cost (31). Alternatively, $\tau = \frac{\alpha_K}{\alpha_M}$ can be treated as a structural parameter to be estimated, as in the baseline specification. While this latter approach produces qualitatively similar results to those in Tables I1 and I2, the estimates of $\frac{1}{1-\rho}$ and α_K are unreasonably small. We interpret this as evidence of the challenges associated with separately identifying these two parameters using the ACF-style estimator.

TABLE I1. Estimates of Production Function Parameters

$\frac{1}{1-\rho}$	$\frac{1}{1-\theta}$	α_L	α_M	α_K	α_S	α_U	σ_ε
0.445	0.709	0.199	0.779	0.022	0.320	0.680	0.257
(0.107)	(0.027)	(0.003)	(0.002)	(0.0001)	(0.003)	(0.003)	(0.014)

NOTE.– This table reports the estimates of the model's structural parameters. Standard errors are calculated using a non-parametric bootstrap clustered at the establishment level. We draw 1,000 bootstrap samples with replacement and re-estimate the structural model for each sample. Out of these, 991 simulations successfully converged.

we find that exporting increases unskilled labor-augmenting productivity both in absolute terms and relative to skilled productivity. Combined with the gross complementarity between skilled and unskilled labor, this biased productivity effect leads to a relative increase in the demand for skilled labor. Moreover, the results validate our assumption that each productivity term follows an independent autoregressive process, as the influence of lagged values of other efficiency terms on any given efficiency term is either small or statistically insignificant.

TABLE I2. Estimates of the Productivity Markov Process Coefficients

	$\ddot{\omega}^K$	$\ddot{\omega}^S$	$\ddot{\omega}^U$
$\ddot{\omega}^K_{-1}$	0.760	-0.016	-0.029
	(0.025)	(0.021)	(0.031)
$\ddot{\omega}^S_{-1}$	-0.015	0.841	0.015
	(0.004)	(0.008)	(0.004)
$\ddot{\omega}^U_{-1}$	-0.034	0.028	0.916
	(0.008)	(0.012)	(0.008)
e_{-1}	0.062	0.038	0.181
	(0.038)	(0.067)	(0.051)
i_{-1}	-0.066	-0.109	0.029
	(0.033)	(0.037)	(0.035)
$e_{-1}i_{-1}$	-0.045	-0.031	-0.018
	(0.038)	(0.066)	(0.052)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

NOTE.– This table presents the coefficients for the productivity Markov process. Standard errors are computed using a non-parametric bootstrap clustered at the establishment level. We draw 1,000 bootstrap samples with replacement and re-estimate the structural model for each sample. Out of these, 991 simulations successfully converged.