Exporting and Productivity Dynamics in the Chinese Footwear Industry*

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Abstract

Revenue-based productivity measures confound physical efficiency with output prices. To recover physical productivity, I embed a CES demand system with destination-specific elasticities into a production-function framework and apply it to Chinese footwear firms from 2000 to 2006. After purging the price component, ordinary exporters are more productive than non-exporters. By contrast, pure processing trade firms, which account for more than half of all exporters, are substantially less productive, a pattern obscured by revenue-based measures. While revenue productivity shows no significant response to tariff reductions, physical productivity reveals sizable within-firm gains from trade liberalization. These findings imply that revenue-based evaluations overstate the performance of processing exporters and understate the productivity gains from liberalization.

Keywords: Physical productivity, multi-destination demand, trade liberalization, processing trade

JEL codes: F14, D43, L25

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1 Introduction

Two well-established empirical regularities characterize the relationship between trade and firm performance. First, exporters tend to have higher measured productivity than non-exporters, consistent with models of self-selection into export markets(Melitz, 2003).[1] Second, trade liberalization, typically measured by tariff reductions, tends to raise measured productivity at the firm level. This paper asks whether these regularities hold up in China once a critical measurement problem is addressed: the confounding of physical productivity with output prices in revenue-based productivity measures.

This question is particularly important in China, where the standard patterns appear to break down. In labor-intensive industries, Chinese exporters are often less productive and sell less domestically than non-exporters. In addition, the distribution of export intensity is U-shaped, with a disproportionate mass of firms exporting nearly all of their output. These patterns differ sharply from the evidence for the United States and other OECD economies. Two features of the Chinese context suggest why. First, on the measurement side, revenue-based productivity combines quantity efficiency with output prices, as emphasized by Klette and Griliches (1996). If exporters and non-exporters face systematically different demand conditions, then revenue-based productivity will mismeasure underlying efficiency. Second, on the institutional side, China's processing trade regime allows firms to import intermediate inputs duty-free as long as the final output is entirely re-exported. This creates a distinct selection mechanism: low-productivity firms that would not otherwise profitably export may enter foreign markets precisely to exploit the tariff exemption, rather than because they are productive enough to cover the fixed costs of exporting.

To disentangle these forces, I develop a multi-destination production-function framework that embeds a CES demand system with destination-specific elasticities. The framework extends De Loecker (2011)'s single-market approach to a setting in which firms simultaneously serve multiple export destinations. It recovers physical productivity from standard firm-level production surveys matched to customs records, without requiring firm-level quantity or price data. Identification of destination-specific demand elasticities relies on two sources of variation: cross-destination and intertemporal variation in tariff protection, and differential changes in aggregate import demand across destinations. Because each

[1] Empirical support includes Bernard and Wagner (1997) for the US, Van Biesebroeck (2005) for sub-Saharan Africa, and Aw et al. (2000) for Korea, and De Loecker (2007) additionally finds productivity gains upon export entry for Slovenian firms.

Chinese footwear firm accounts for a negligible share of any destination market, these destination-level shifters are plausibly exogenous to firm-level behavior. On the production side, I address the simultaneity between input choices and unobserved productivity using a control-function approach with intermediate inputs as the proxy variable. The productivity law of motion is identified from the orthogonality of predetermined capital and lagged flexible inputs to current productivity innovations.

I apply this method to the Chinese footwear industry from 2000 to 2006, spanning China's WTO accession and the peak of the processing trade regime. The analysis combines firm-level production data from the Annual Survey of Manufacturing (ASM) with transaction-level customs records and destination-specific tariff data. The industry is particularly well-suited to this setting for two reasons. First, footwear exporters serve a diverse set of destination markets with substantial variation in tariffs, aggregate demand, and price levels, providing the variation needed to identify the demand system. Second, processing trade accounts for roughly half of all exporting firms and more than half of total export value, making footwear an ideal setting for studying how the regime shapes productivity measurement and firm dynamics.

The empirical analysis yields three main findings. First, once prices are purged, firms engaged in ordinary trade are more physically productive than non-exporters, consistent with the Melitz (2003) framework. This productivity advantage is largely obscured in revenue-based measures. Second, pure processing trade firms are substantially less physically productive than other exporters, even though revenue-based productivity makes them appear similar because they disproportionately serve high-price export markets. This finding is consistent with Yu (2015), who emphasize that the tariff exemption embedded in processing trade alters export selection. Third, tariff reductions generate significant within-firm productivity gains for ordinary exporters in physical productivity, even though no comparable gains appear in revenue-based productivity. These gains reflect both increased competitive pressure from lower output tariffs and cheaper access to imported intermediates through lower input tariffs. By contrast, processing trade firms benefit less from tariff liberalization, consistent with their pre-existing exemption from input tariffs.

This paper contributes to three strands of the literature. First, it contributes to work on the estimation of physical productivity when firm-level prices are unobserved. Revenue-based TFP conflates physical efficiency with demand-side forces (Klette and Griliches, 1996; Katayama et al., 2009), and recent evidence suggests that much of the variation in revenue productivity reflects demand and markups rather than production efficiency (Forlani et al., 2023). When firm-level prices are unavailable, De Loecker (2011)'s strategy of embedding demand into the production-function framework provides a tractable solution. I extend this approach to a multi-destination setting and identify destination-specific demand elasticities using variation in tariffs and aggregate import demand across regions, which are available and plausible exogenous macro variables. My results show that this correction materially changes the substantive conclusions about exporter productivity and the effects of trade liberalization.

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Second, the paper contributes to the literature on trade liberalization and firm productivity. Brandt et al. (2017) document differential responses to tariff cuts during China's WTO accession, and De Loecker et al. (2016) show that ignoring price effects can bias productivity estimates under trade reform. Recent work further emphasizes the importance of demand-side forces in shaping exporter dynamics: Fitzgerald et al. (2024) show that post-entry export growth is driven primarily by quantities rather than markups; Rodrigue and Tan (2019) find that Chinese exporters adjust prices and quality to build demand; and Li (2018) shows that demand uncertainty plays a larger role than productivity in export dynamics. Building on this literature, I show that tariff reductions generate significant within-firm gains in physical productivity for ordinary exporters, even though such gains are largely absent in revenue-based measures. This distinction is important for evaluating the effects of trade liberalization because revenue-based productivity understates the productivity gains associated with tariff reductions.

Third, the paper contributes to the literature on China's processing trade regime. Prior work has primarily studied processing trade through structural selection models (Yu, 2015; Manova and Yu, 2016) or sample exclusion strategies (Dai et al., 2016). I take a different approach by directly recovering the physical productivity distribution of processing firms. The results show that processing firms are, on average, less productive than ordinary exporters and experience smaller within-firm gains from tariff reductions, while also displaying substantial heterogeneity that is obscured by revenue-based measures. In this sense, the paper provides micro-level evidence consistent with Brandt et al. (2021), who document sizable aggregate welfare costs of the regime.

The remainder of this paper is organized as follows. Section 2 provides background on the Chinese footwear market, the processing trade regime, and describes the three datasets used in the analysis. Section 3 presents the production function framework and the demand system used to estimate physical productivity. Section 4 discusses the estimation and identification strategy. Section 5 presents the main results. Section 6 concludes.

2 Institutional Background and Data

This section describes the institutional features of China's processing trade regime that are central to the analysis, the three datasets used in the empirical work, and key descriptive statistics on exporting patterns in the footwear industry.

2.1 processing trade and special tariff treatment

Processing trade refers to business activities in which a firm imports raw materials or intermediate inputs from abroad, processes or assembles them domestically, and re-exports the finished products. Like many labor-intensive sectors, the footwear industry is subject to a special tariff regime that has been in place since the early 1980s. Under this regime, imported materials used for processing trade are duty-free, but the firm is prohibited from selling the resulting output on the domestic market.

This institutional arrangement gives rise to three types of trade regimes at the firm level. Ordinary trade firms do not use any duty-free imported inputs and pay tariffs on imported inputs. Pure processing trade firms enjoy tariff exemptions on all imported inputs but must re-export all output. The third type is a hybrid that engages in both ordinary and processing trade. The footwear industry provides a particularly suitable setting for studying these trade regimes. Footwear production is labor-intensive, strongly export-oriented, and closely integrated into global buyer-supplier networks, making processing trade especially prevalent during this period. These features also make the industry a useful laboratory for examining how trade regime choice interacts with exporting behavior and productivity.

As part of its WTO accession, China's average output tariff fell from 43.2% in 1992 to 15.3% in 2001 (Brandt et al., 2017). The footwear industry followed the same trajectory: as Figure 1 shows, output tariffs declined steadily over the sample period, putting downward pressure on domestic output prices. Importantly, the effect of tariff reductions on processing-trade firms differs from the standard predictions in the literature, since these firms were already exempt from input tariffs and could not sell domestically. Therefore, tariff liberalization operated through different channels for ordinary-trade and processing-trade firms.

2.2 Data

The empirical analysis combines three panel datasets covering 2000–2006: firm-level production data, transaction-level customs records, and product-level tariff data.[2]

Annual Survey of Manufacturing (ASM). The ASM is collected annually by China's National Bureau of Statistics and covers all state-owned industrial firms and non-state-owned firms with annual sales above 5 million RMB. It reports standard firm-level production variables, such as revenue, employment, fixed assets, intermediate inputs, and export delivery value. It is comparable to the U.S. Longitudinal Research Database. Aggregates for employment, sales, capital, and exports match almost perfectly the totals reported in China's Statistical Yearbook. Two features warrant discussion. First, the above-scale sampling threshold

[2]The sample period is determined by data availability. The ASM files for 2008 onward are missing key variables (intermediate inputs in 2008; revenue, wages, and fixed assets in 2009; employment in 2010–2011), and the Chinese Monthly Customs Transactions data begin in 2000.

means the data cannot be used to study firm exit, and small firms that appear in the sample may be disproportionately productive. Second, the ASM records legal units rather than establishments, but 97% of footwear firms contain only one industrial activity unit, making this effectively a plant-level dataset.

Chinese Monthly Customs Transactions. This dataset records the universe of Chinese trade transactions at the HS 6-digit product level. Each observation is a firm-product-destination-month combination, with information on export value, quantity, unit value, and trade regime (ordinary trade, processing with imported materials, or processing with supplied materials, as described in Section2.1). I retain transactions with HS codes beginning with 64 (footwear) and exclude transactions by trading intermediaries, which cannot be linked to production data.[3]

Tariff and trade data. I collect product-level tariff data from the WITS TRAINS database at the HS 6-digit level for all footwear products across all available countries from 2000 to 2006. I use the volume-adjusted effectively applied tariff as the measure of trade protection. Aggregate import values at the footwear category level are obtained from the UN COMTRADE database and used to construct destination-level demand shifters. The construction of the firm-specific tariff protection measure and the aggregate demand shifters is described in Section 4.

From the ASM, I select firms in Chinese Industrial Classification (CIC) codes 18 (textiles), 19 (leather), 29 (rubber), and 30 (plastics), retaining only those whose reported main products are footwear. Following Brandt et al. (2017), I exclude firms with fewer than 8 employees, drop observations with negative or missing capital, sales, or intermediate inputs, and exclude firms with intermediate-input-to-sales ratios outside $[0.5, 5]$, removing 334 additional observations. From the customs data, I retain all non-intermediary footwear transactions (HS-2 code 64) and aggregate them to the firm-destination-year level.

A central challenge is that the ASM and customs datasets share no common firm identifier. I match them using firm name and geographic information, following the procedure described in Yu (2015). Within each dataset, I use the firm's legal identification number to link observations across years. Table 1 shows that the matching procedure successfully links approximately 32–36% of ASM footwear firms to customs records in any given year. However, this understates the true share of exporters because many firms export indirectly through trading

[3]Trading companies are potentially useful as they provide information about the countries Chinese firms are in contact with. I exclude them because they cannot be matched to the ASM.

intermediaries and therefore do not appear in the customs data under their own name. Prior to 2004, many private firms could only export through third parties; even after 2004, indirect exporting through intermediaries remained common.

To address this, I construct two measures of export status. The first, Exp_d, equals one for firms successfully matched to the customs dataset, these are direct exporters that establish their own foreign buyer relationships. The second, *Exp*, additionally includes firms that report a positive export delivery value in the ASM but cannot be found in the customs data. These firms are classified as indirect exporters using trading intermediaries.[4] Among ASM exporters identified by *Exp*, only about 57% can be matched to customs records (Exp_d), implying that 43% in the footwear industry relied on intermediaries during this period.

For the remainder of the analysis, I define exporters using the broader measure *Exp* and use Exp_d to distinguish direct exporters from those using intermediaries. This distinction matters for two reasons. First, excluding indirect exporters would overstate non-exporters' domestic sales, since these firms do export but through channels not recorded in the customs data. Second, the customs data provide destination-level information only for Exp_d firms; for indirect exporters, I construct a separate intermediary market to account for their export revenue, as described in Section 4.

The production function estimation requires measures of output, labor, intermediate inputs, and capital. Output is measured by total revenue. Labor is measured by the number of employees. Intermediate inputs are reported directly in the ASM. For the capital stock, I follow the perpetual inventory method of Brandt et al. (2014), which constructs real capital stocks from reported fixed assets using province-by-sector nominal growth rates and an investment price deflator, with a depreciation rate of $\delta = 0.09$.[5]

To express nominal variables in constant prices, I construct two deflators following Brandt et al. (2014), with 2004 as the base year. The output deflator for the domestic footwear market exploits firm-level price information available in the ASM for 2000–2003. During this period, firms reported output in both nominal and real prices, providing a firm-level price index that is aggregated to the segment level using current-price output as weights. For 2004–2006, the deflator is extended using the 2-digit ex-factory price index from the China Statistical Yearbook. The input deflator is constructed using the output deflators and input

[4] In 2004, the ASM did not collect export delivery value. For that year, I use the average export delivery value of each firm in neighboring years as a proxy.

[5] The methodology and code are available at `https://feb.kuleuven.be/public/u0044468//CHINA/appendix/`. Details are provided in the supplementary material.

shares from the 2002 National Input–Output table.[6]

From the customs data, I observe each matched firm's export revenue, quantity, and unit value by destination and trade regime. This allows me to classify firms into ordinary trade and processing trade, and to construct destination-level revenue shares needed for the demand system in Section 3.

Table 2 reports summary statistics for the estimation sample of 17,442 firm-year observations. The distributions of revenue, capital, and intermediate inputs are heavily right-skewed: median revenue is 18.3 million RMB, well below the mean of 52.8 million, reflecting the presence of a few very large producers. The median firm employs 205 workers. Using the direct customs-match definition (Exp_d), about one-third of firm-year observations are exporters; under the broader ASM-based measure (Exp), the share rises to one-half.

2.3 Exporting patterns of Chinese exporters in the footwear industry

U-shaped export intensity In the standard Melitz (2003) framework, productive firms self-select into exporting but continue to serve the domestic market, so the model predicts that most exporters should have a relatively low export intensity. Empirical evidence from the US and other OECD countries broadly supports this prediction. A well-documented departure from this pattern arises in China, where the distribution of export intensity is U-shaped: while many firms export only a small share of their output, a large mass of firms export virtually all of it. Figure 2 shows that this U-shaped pattern is present in the footwear industry as well. The left panel plots export intensity, defined as foreign sales divided by total revenue for all exporters, revealing concentrations of firms at both ends of the distribution. Because pure processing trade firms are prohibited from selling in the domestic market, they mechanically have an export intensity of nearly 100%. The right panel excludes these firms, yet the U-shape persists: a sizable group of ordinary-trade exporters also ship the vast majority of their output abroad. This suggests that the pattern is not driven solely by the institutional constraints of processing trade.

Prominence of processing trade Processing trade is a distinctive feature of Chinese manufacturing. As Yu (2015) argues, low-productivity firms may self-select into processing trade in order to take advantage of tariff exemptions on imported

[6] Details of the deflator construction are provided in supplementary material.

intermediate inputs, potentially weakening the standard positive relationship between productivity and exporting predicted by heterogeneous-firm models.

Table 3 shows that processing trade is quantitatively important in the footwear industry throughout the sample period. Pure processing firms account for roughly half of all exporters: their share ranges from 40.1% in 2004 to 58.0% in 2005, and remains at 57.5% in 2006. They also account for a disproportionately large share of export value. In most years, pure processing firms generate more than half of total exports, with export shares of 56.7% in 2000, 60.8% in 2004, 61.4% in 2005, and 60.9% in 2006. This pattern indicates that processing-trade firms are not only numerous, but also economically important in aggregate exports.

At the same time, the regime-transition evidence suggests that trade status is far from fixed. Table 4 shows strong persistence within each regime, but also nontrivial switching across regimes. Among firms that are pure ordinary traders in year t, 92.86% remain pure ordinary traders in year $t+1$, while 7.14% move into the mixed regime. Mixed firms are the least stable group: 86.77% remain mixed in the following year, but 4.78% switch to pure ordinary trade and 8.45% switch to pure processing trade. Pure processing firms are also highly persistent, with 86.82% remaining pure processing traders in the next year, although 12.98% transition into the mixed regime and 0.20% switch directly into pure ordinary trade.

Taken together, these two tables suggest that processing trade should not be treated as a peripheral margin. It accounts for a large fraction of both exporting firms and export value, while also serving as part of a dynamic transition process across trade regimes. One interpretation is that some firms enter foreign markets through processing trade, accumulate production experience and buyer relationships, and later expand into ordinary trade while remaining highly export-oriented. If so, the standard self-selection mechanism—in which more productive domestic firms become exporters—may need to be complemented by a dynamic pathway in which firms build export capability through processing trade before switching regimes. This is why the analysis distinguishes between processing-trade and ordinary-trade exporters rather than pooling them together.

Broad destination-market participation The footwear industry is also characterized by broad participation across destination markets. Table 5 shows that exporters are active across all major foreign regions throughout the sample period, including East Asia and Pacific, North America, the EU, Latin America, Africa, and non-EU Europe. For example, around one-quarter of exporters serve East

Asia and Pacific, while the share serving the EU rises from 17.7% in 2000 to 21.9% in 2006. At the same time, many exporters also serve the domestic market or export indirectly through intermediaries. These patterns indicate that footwear exporters operate across a diverse set of markets with different tariff levels, demand conditions, and price environments, which is central to the identification of the demand system developed below.

3 Model

I model the supply and demand for horizontally differentiated footwear varieties produced by single-product firms and sold in multiple destination markets. The model yields an estimating equation that links observed revenues to inputs and destination-specific demand shifters, allowing me to recover physical productivity when firm-level quantities are not observed.

Environment Firms are indexed by i, destinations by d, and time by t. Each firm produces a single footwear variety in one of four segments, s in textile, leather, rubber, plastic. Let D_{it} denote the set of destination markets served by firm i in period t, which may include the domestic market. This formulation differs from standard exporting models in which the domestic market is a default option for all firms. In my setting, pure processing-trade firms are prohibited from selling domestically.

3.1 Single-destination benchmark

I begin with the benchmark case in which a firm serves only one destination market. This benchmark clarifies how demand-side variation enters revenue and productivity measurement.

Demand. In each destination market d, consumers aggregate differentiated footwear varieties with a CES demand system:

$$U_t^d = \left[\sum_{j \in J_t^d} \left(V_{jt}^d \right)^{1/\eta} \left(Q_{jt}^d \right)^{(\eta-1)/\eta} \right]^{\eta/(\eta-1)}$$

where $\eta > 1$ is the elasticity of substitution across varieties, V_{jt}^d is a variety-specific demand shifter, and J_t^d is the set of varieties available in destination d

at time t. Let $\tilde{P}^d_{jt}$ denote the consumer price of variety j in destination d, and let R^d_t denote total expenditure on imported footwear in that market.

Cost minimization implies the standard CES demand function for firm i:

$$Q^d_{it} = Q^d_t \left(\frac{\tilde{P}^d_{it}}{P^d_t} \right)^{-\eta} V^d_{it}, \qquad Q^d_t \equiv \frac{R^d_t}{P^d_t},$$

where the destination-specific price index is

$$P^d_t = \left[\sum_{j \in J^d_t} (\tilde{P}^d_{jt})^{1-\eta} V^d_{jt} \right]^{1/(1-\eta)}.$$

Taking logs gives

$$q^d_{it} = q^d_t - \eta(\tilde{p}^d_{it} - p^d_t) + \xi^d_{it},$$

where $\xi^d_{it} \equiv \ln V^d_{it}$ is a firm-destination demand shock.

I assume that the consumer price in destination d differs from the producer price received by the firm because of destination-specific trade costs:

$$\tilde{p}^d_{it} = p^d_{it} + \tau^{d,s}_t,$$

where $\tau^{d,s}_t$ captures the ad valorem trade-cost wedge for segment s in destination d at time t. Substituting this expression into demand yields

$$q^d_{it} = q^d_t - \eta \left(p^d_{it} + \tau^{d,s}_t - p^d_t \right) + \xi^d_{it}.$$

Production. Firm i produces total output Q_{it} using labor L_{it}, materials M_{it}, and capital K_{it} according to a Cobb–Douglas production function:

$$Q_{it} = L^{\alpha_l}_{it} M^{\alpha_m}_{it} K^{\alpha_k}_{it} \exp(\omega_{it} + u_{it}), \tag{1}$$

where ω_{it} is firm productivity and u_{it} is an i.i.d. transitory shock. In logs,

$$q_{it} = \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + \omega_{it} + u_{it}.$$

Revenue and revenue-based productivity. Because physical quantities are not observed in the production data, a standard approach is to proxy output using deflated revenue. Under imperfect competition, however, deflated revenue reflects not only physical productivity but also firm-specific prices and demand conditions.

Using the demand system above, the inverse demand in destination d is

$$p_{it}^{d} = -\frac{1}{\eta} q_{it}^{d} + \frac{1}{\eta}(q_t^d + \xi_{it}^d) + p_t^d - \tau_t^{d,s}.$$

Hence log revenue in destination d is

$$r_{it}^{d} = p_{it}^{d} + q_{it}^{d} = \frac{\eta - 1}{\eta} q_{it}^{d} + \frac{1}{\eta}(q_t^d + \xi_{it}^d) + p_t^d - \tau_t^{d,s}.$$

Defining destination-deflated revenue as $\tilde{r}_{it}^{d} \equiv r_{it}^{d} - p_t^d$,

$$\tilde{r}_{it}^{d} = \frac{\eta - 1}{\eta} q_{it}^{d} + \frac{1}{\eta}(q_t^d + \xi_{it}^d) - \tau_t^{d,s}. \tag{2}$$

Equation (2) makes clear why revenue-based productivity is problematic in this setting. Relative to physical output, revenue reflects not only production efficiency but also destination-specific demand shifters, firm-level demand shocks, and trade-cost wedges. This concern is particularly important in my setting because tariff liberalization directly affects prices and therefore contaminates productivity measures based on deflated revenue alone.

3.2 Firms Serving Multiple Markets

Most footwear firms in the data sell to several destination markets simultaneously. Rather than assuming a fixed allocation of output across destinations, I model the intensive-margin decision explicitly, allowing the demand elasticity η^d to vary across destination markets.

Allocation problem. Given total output Q_{it} and a predetermined destination set D_{it}, firm i allocates quantities across markets to maximize total revenue:[7]

$$\max_{\{Q_{it}^d\}_{d \in D_{it}}} \sum_{d \in D_{it}} P_{it}^d Q_{it}^d \qquad \text{s.t.} \quad \sum_{d \in D_{it}} Q_{it}^d = Q_{it}.$$

Single-market deflated revenue. In each market d, consumers have CES preferences with a destination-specific elasticity of substitution η^d. Using the CES

[7]Because total output Q_{it} is given, the production cost $c_{it}Q_{it}$ is sunk at the allocation stage. I assume that the marginal cost c_{it} is the same for units shipped to any destination and do not model how Q_{it} is determined.

inverse demand, the deflated revenue from destination d is

$$\tilde{r}^d_{it} = \frac{\eta^d - 1}{\eta^d}\, q^d_{it} + \frac{1}{\eta^d}(q^d_t + \xi^d_{it}) - \tau^{d,s}_t. \tag{3}$$

Aggregating deflated revenue. Summing (3) across all active destinations and writing $q^d_{it} = q_{it} + (q^d_{it} - q_{it})$, where $q_{it} = \ln\bigl(\sum_{d \in D_{it}} Q^d_{it}\bigr)$ is log total output:

$$\tilde{r}_{it} = \underbrace{\sum_{d \in D_{it}} \frac{\eta^d - 1}{\eta^d}(q^d_{it} - q_{it})}_{C_{it}} + \bar{\sigma}_{it}\, q_{it} + \sum_{d \in D_{it}} \frac{1}{\eta^d}(q^d_t + \xi^d_{it}) - \sum_{d \in D_{it}} \tau^{d,s}_t, \tag{4}$$

where $\bar{\sigma}_{it} \equiv \sum_{d \in D_{it}} \frac{\eta^d - 1}{\eta^d}$ aggregates the destination-specific revenue-to-quantity coefficients.

Constructing C_{it} from observed revenues. The correction term C_{it} involves log quantities q^d_{it}, which are not directly observed. The markup pricing condition provides the necessary link. With destination-specific η^d, the optimal markup in market d is $\eta^d/(\eta^d - 1)$, so that $R^d_{it} = \frac{\eta^d}{\eta^d - 1} c_{it}\, Q^d_{it}$, where c_{it} is the common marginal cost. Inverting gives $Q^d_{it} = \frac{\eta^d - 1}{\eta^d} \frac{R^d_{it}}{c_{it}}$, and hence

$$q^d_{it} - q_{it} = \ln \frac{\eta^d - 1}{\eta^d} + \ln R^d_{it} - \ln\Bigl(\textstyle\sum_{d' \in D_{it}} \frac{\eta^{d'} - 1}{\eta^{d'}} R^{d'}_{it}\Bigr),$$

where the marginal cost c_{it} cancels. Substituting back into the definition of C_{it}:

$$C_{it} = \sum_{d \in D_{it}} \frac{\eta^d - 1}{\eta^d} \ln\left(\frac{\frac{\eta^d - 1}{\eta^d} R^d_{it}}{\sum_{d'} \frac{\eta^{d'} - 1}{\eta^{d'}} R^{d'}_{it}} \right). \tag{5}$$

This is a weighted sum of log markup-adjusted revenue shares, fully determined by observed destination-level revenues R^d_{it} and the demand parameters η^d. When firms spread revenue roughly equally across destinations and the η^d do not vary too much, the markup-adjusted shares are approximately $1/n_{it}$, giving $C_{it} \approx -\bar{\sigma}\, n_{it} \ln n_{it}$. In estimation, I therefore control for the number of active destinations n_{it} to absorb the primary variation in both C_{it} and the scaling factor $\bar{\sigma}_{it}$.

Estimating equation. Substituting the production function (1) into (4):

$$\tilde{r}_{it} = C_{it} + \beta_l\, l_{it} + \beta_m\, m_{it} + \beta_k\, k_{it} + \sum_{d \in D_{it}} \frac{1}{\eta^d}\, q_t^d + \omega_{it}^* + \xi_{it}^* + u_{it}^*, \tag{6}$$

where the composite coefficients are

$$\beta_h = \bar{\sigma}_{it}\, \alpha_h \quad (h \in \{l, m, k\}), \qquad \omega_{it}^* = \bar{\sigma}_{it}\, \omega_{it}, \qquad u_{it}^* = \bar{\sigma}_{it}\, u_{it},$$

and $\xi_{it}^* = \sum_{d \in D_{it}} \frac{1}{\eta^d}\, \xi_{it}^d - \sum_{d \in D_{it}} \tau_t^{d,s}$ absorbs the unobserved firm-destination demand shocks and the trade-cost wedges.

Equation (6) highlights three features of the multi-market setting. First, each destination's aggregate demand shifter q_t^d enters with its own coefficient $1/\eta^d$, allowing the data to reveal destination-specific demand elasticities rather than imposing a common elasticity across all markets. Second, the input coefficients β_h are reduced-form parameters that bundle the technology parameters α_h with the demand-side scaling $\bar{\sigma}_{it}$, which depends on the firm's destination set through both the number and composition of active markets. Third, unobserved productivity ω_{it}^* is scaled by $\bar{\sigma}_{it}$, so firms selling to more destinations mechanically generate higher revenue for a given level of physical productivity. The n_{it} control, together with the destination-specific demand shifters, absorbs the demand-side variation that would otherwise contaminate productivity estimates.

Predetermined destination sets. Throughout the derivation, I take each firm's destination set D_{it} as given. This parallels the standard timing assumption on capital in the production-function estimation literature: firms choose which markets to serve before observing current-period productivity and demand shocks. The assumption is particularly natural in the Chinese footwear industry, where processing trade arrangements and long-term buyer relationships make destination sets persistent. Formally, D_{it} may depend on lagged productivity ω_{it-1}, but since the Markov process for productivity (9) already conditions on ω_{it-1}, this dependence does not bias the estimates.

4 Estimation Strategy

Taking Equation (6) to the data requires three steps: decomposing the unobserved demand shocks so that productivity can be separated from demand-side variation, constructing the empirical counterparts of the aggregate demand shifters and the tariff protection measure, and addressing the endogeneity of inputs through a control-function approach. I describe each in turn.

4.1 Decomposing the composite demand error

Recall from Equation (6) that the composite error $\xi^*_{it} = \sum_{d \in D_{it}} \frac{1}{\eta^d} \xi^d_{it} - \sum_{d \in D_{it}} \tau^{d,s}_t$ aggregates the destination-level demand shocks and trade-cost wedges into a single reduced-form term. Left uncontrolled, this term would contaminate the productivity residual. Following De Loecker (2011), I decompose it into observable and residual components:

$$\xi^*_{it} = \delta_{dest} + \delta_s + \delta_t + \tau\, qr_{it} + \tilde{\xi}_{it}, \tag{7}$$

where δ_{dest} captures destination fixed effects at the subregion and country level, δ_s captures segment fixed effects (leather, textile, rubber, and plastic), and δ_t captures year fixed effects. These fixed effects absorb time-invariant demand differences across destinations and segments as well as common aggregate shocks. As discussed in Section 2.3, I define nine destination regions—including the domestic market and a separate intermediary market for firms exporting through trading companies—and control for finer geographic variation through subregion and country fixed effects.[8]

The key remaining term is the firm-specific tariff protection measure qr_{it}, which enters the composite error because it shifts residual demand contemporaneously, and also affects future productivity through the law of motion. Because firms serve different destination markets with different levels of trade protection, qr_{it} varies across firms and provides demand-side variation that is plausibly exogenous to individual firm behavior.

4.2 Empirical measures

Firm-specific tariff protection. I construct the tariff protection measure in two steps. First, I compute a market-level protection index for each destination region d:

$$qr^d_t = \sum_f a^d_{ft}\, tariff^d_{ft},$$

where $tariff^d_{ft}$ is region d's tariff on partner country f in the footwear industry at time t, and a^d_{ft} is the share of country f in region d's total footwear imports. I

[8]For a detailed discussion of the market definition, see Appendix A.

measure qr_t^d using the volume-adjusted effectively applied tariff from the WITS TRAINS database. A higher qr_t^d indicates a more protected market.

Second, I aggregate the market-level indices into a firm-specific exposure measure using each firm's revenue shares across destinations:

$$qr_{it} = \sum_d \frac{W_{it}^d}{W_{it}} qr_t^d,$$

where W_{it}^d / W_{it} is the share of firm i's revenue earned in region d. Using revenue weights captures the firm's intensive-margin allocation across markets.[9] For indirect exporters using trading intermediaries, the protection level is a weighted average across all foreign regions, with weights given by China's aggregate footwear export shares. Figures 3 and 4 show that firms face the highest protection in the African market and the lowest in non-EU Europe, and that average protection declines through 2005 before rising slightly due to tariff increases in East Asia and Pacific.

Price index. The price index p_t^d used to deflate destination-level revenue is the import price index (IPI) at each destination region, collected from the CEIC database. I construct a weighted average of representative countries within each region to ensure consistent trends. For the domestic market, I use the output deflator from Brandt et al. (2014). For the intermediary market, the price index is a weighted average of all foreign regions' price indices, with weights given by China's footwear export shares. Because the price index is relative to a base year within each region, it captures within-region variation over time; cross-region level differences are absorbed by the destination fixed effects.

Aggregate demand shifters. For each foreign destination, the aggregate demand shifter q_t^d is measured by the total import value of footwear products at the region level in each period, obtained from the WITS UN COMTRADE database. For the domestic market, I follow De Loecker (2011) and compute aggregate demand as industry-weighted deflated revenue: $Q_t^{domestic} = \sum_i ms_{it} R_{it} / P_t$, where ms_{it} is firm i's market share. For the intermediary market, aggregate demand is a weighted average of all foreign regions' demand using China's export shares as weights. Identification of the destination-specific demand elasticities η^d relies on the time variation in these aggregate demand shifters across regions. As Figure 6

[9] I also considered simple averages; revenue weights yield the most precisely estimated coefficients.

shows, there is substantial cross-regional variation: China's domestic market has the highest demand, followed by North America, while Africa has the lowest. The differential time paths across regions, not just their levels, which are absorbed by the destination fixed effects, are what identify the separate $\beta_q^d = 1/\eta^d$ coefficients. Since each firm's share in any region's total footwear imports is negligible, the aggregate demand shifters can be treated as exogenous.

Because the price index p_t^d is defined relative to a base year within each region, it captures within-region variation over time but does not permit meaningful cross-region level comparisons. The destination fixed effects absorb these level differences, so the estimation relies only on how prices move within each region over the sample period.

4.3 Estimation procedure

Combining the demand decomposition (7) with the structural equation (6), the empirical specification is:

$$\tilde{r}_{it} = \beta_n n_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \sum_{d \in D_{it}} \beta_q^d q_t^d + \tau qr_{it} + \delta_d + \delta_g + \delta_t + \omega_{it}^* + \epsilon_{it}, \tag{8}$$

where $\beta_q^d = 1/\eta^d$ is the destination-specific demand coefficient, β_n absorbs the variation in C_{it} and $\bar{\sigma}_{it}$ through the number of active destinations (as discussed in Section 3.2), q_t^d is set to zero when firm i does not sell to region d at time t, and ϵ_{it} collects the idiosyncratic production and demand shocks.

Tariff protection qr_{it} affects firms through two channels: it shifts residual demand contemporaneously, and it affects future productivity as firms respond to increased competition by eliminating inefficiencies. Following De Loecker (2013), I also include a dummy variable $dexp_{it}$ for export experience, allowing the model to detect learning by exporting. The law of motion for productivity is therefore:

$$\omega_{it} = g(\omega_{it-1}, qr_{it-1}, dexp_{it-1}) + \nu_{it}, \tag{9}$$

which I approximate with a second-order polynomial in practice.

First stage. To address the simultaneity of input choices and unobserved productivity, I adopt the control-function approach of Ackerberg et al. (2015). Following Levinsohn and Petrin (2003), I use intermediate inputs as the proxy variable to invert the productivity function, which avoids the requirement of positive investment that limits the Olley and Pakes (1996) estimator. In the first stage, I estimate a third-order polynomial in all right-hand-side variables of (8) to obtain $\hat{\phi}_t$, which separates the sum of observable demand shocks and unobserved productivity from the idiosyncratic error.[10] Following Ackerberg et al. (2015), no coefficients are identified in the first stage.

Second stage. In the second stage, the GMM estimates the production function coefficients $(\beta_l, \beta_m, \beta_k)$, the destination-specific demand coefficients (β_q^d), the tariff coefficient (τ), and the segment and year fixed effects (δ_g, δ_t) as free parameters. Ideally, the estimation would also include finer destination fixed effects to absorb demand heterogeneity within regions. In practice, the nonlinear GMM cannot accommodate this many parameters, so I control for destination effects only at the region level through the first-stage polynomial. The region-level effects are carried through $\hat{\phi}_t$ rather than estimated as separate parameters in the GMM.

For any candidate parameter vector, I recover productivity as:

$$\omega_{it} = \hat{\phi}_t - \beta_n\, n_{it} - \beta_l\, l_{it} - \beta_m\, m_{it} - \beta_k\, k_{it} - \sum_d \beta_q^d\, q_t^d - \tau\, qr_{it} - \delta_d - \delta_g - \delta_t,$$

and compute the innovation $\nu_{it} = \omega_{it} - g(\omega_{it-1}, qr_{it-1}, dexp_{it-1})$. I absorb the subregion and country fixed effects in the nonparametric regression of ω_{it} on its lagged values to reduce the dimensionality of the GMM problem.[11]

The parameters are identified by the following moment conditions. First, since no individual firm can influence a region's tariff, the contemporaneous tariff measure is orthogonal to the productivity innovation:

$$E(\nu_{it} \mid qr_{it}) = 0. \tag{10}$$

Second, the standard timing assumptions imply that capital (decided one period ahead) and lagged values of flexible inputs are orthogonal to the current innovation. The full set of GMM conditions is:

$$E\left\{ \nu_{it} \begin{pmatrix} k_{it} \\ m_{it-1} \\ l_{it-1} \\ q_{t-1}^d \\ qr_{it} \end{pmatrix} \right\} = 0. \tag{11}$$

[10]For the detailed assumptions on the input demand equation and the monotonicity condition, see supplementary material.

[11]Because the fixed effects are absorbed in the Markov process, the productivity estimates should be interpreted as within-firm changes over time rather than cross-sectional levels.

I estimate the parameters by minimizing the GMM objective function and use the bootstrap for inference. The demand elasticity parameters $\beta_q^d = 1/\eta^d$ are identified under the assumption that productivity innovations are uncorrelated with lagged aggregate demand in each destination, which is plausible given that these are macro-level variables determined by foreign market conditions.

5 Results

This section presents the main empirical findings in four parts. I first report the production function and demand parameter estimates from the estimation procedure described in Section 4. I then establish that exporters and non-exporters differ systematically in observable characteristics, motivating the need for a physical productivity measure. Next, I compare the physical productivity distributions across firm types and examine aggregate dynamics. Finally, I study the effect of trade liberalization on within-firm productivity dynamics.

5.1 Production function and demand parameter estimates

Table 6 reports production function coefficients under three specifications. The first column estimates an OLS regression of deflated revenue on inputs without correcting for simultaneity. The second applies the ACF proxy approach using a common domestic price deflator. Adding the demand system (column 3) increases the labor and material coefficients noticeably. Since both input demand and output prices respond to demand shocks, the standard proxy approach confounds price variation with productivity variation, biasing the labor and material coefficients downward. The capital coefficient changes little across specifications, as expected given that capital is predetermined.

Table 7 reports the full set of demand parameters estimated by GMM with bootstrapped confidence intervals. The inverse demand elasticity $\beta_q^d = 1/\eta^d$ ranges from 0.427 (Non-EU Europe) to 0.809 (Latin America), implying demand elasticities between -1.24 and -2.34. The East Asia and Pacific coefficient is imprecise, and its 90% bootstrapped confidence interval contains zero. Therefore, I set it to zero in the productivity recovery.[12] The cross-region pattern is economically plausible: Latin America ($\eta^d = -1.24$) and North America ($\eta^d = -1.26$) exhibit the most inelastic demand, suggesting that Chinese footwear faces less

[12] This also applies to the tariff protection coefficient, the time fixed effects, and the fixed effects for the textile and rubber segments.

substitution pressure in these markets, while Non-EU Europe ($\eta^d = -2.34$) is the most elastic. The two domestic markets, China Domestic and China Intermediary, have similar elasticities and sit in the middle of the range, indicating that the domestic-export price wedge is not driven by an extreme elasticity on either side. Among the segment fixed effects, only the plastic segment is significant at -0.995, reflecting the substantially lower revenue of plastic shoe firms relative to leather shoe firms, conditional on inputs. The number-of-destinations coefficient β_n is large and significant, confirming that multi-market firms earn substantially higher revenue after controlling for inputs and demand conditions, consistent with the market-allocation correction C_{it} discussed in Section 3.

The precision of the demand estimates varies across regions. Africa, Latin America, the EU, and the rest of Asia yield tight confidence intervals and economically plausible elasticities; East Asia and the Pacific are imprecise and set to zero. The main elasticity results rely most heavily on the regions with the strongest identifying variation. An alternative specification that collapses regions with limited tariff variation or that relaxes the time-invariance assumption could sharpen the estimates further. They all require balancing precision against the loss of cross-regional heterogeneity, which is central to the identification strategy.

As discussed in Section 4.3, the GMM estimates include segment and year fixed effects but only region-level destination effects, rather than finer subregion or country-level effects. The recovered productivity $\hat{\omega}_{it}$ therefore incorporates unabsorbed destination effects, making productivity levels not directly comparable across firms serving different destination sets. However, for within-firm dynamics, the destination effects cancel when the firm's destination set is stable, so the Markov regressions in Section 5.4 remain valid.

5.2 Exporter characteristics and the case for physical productivity

Before turning to the productivity distributions, I document systematic differences between exporters and non-exporters in observable characteristics. Following Bernard and Bradford Jensen (1999), I estimate the following OLS regression:

$$x_{it} = \alpha + \beta exp_{it} + \gamma l_{it} + \sum_s \delta_s D_s + \sum_p \delta_p D_p + \sum_t \delta_t D_t + \epsilon_{it}$$

where x_{it} denotes firm characteristics (employment, sales, capital per worker, average wage), exp_{it} is a dummy for export status, l_{it} controls for firm size, and D_s,

D_p, and D_t are segment, province, and year fixed effects, respectively.

Table 8 reports the results. Exporting firms are significantly larger and pay higher wages, consistent with Bernard and Bradford Jensen (1999). However, the domestic market performance of exporters is striking: even under the conservative measure Exp_d, exporters' domestic sales are only 8.5% higher than non-exporters, while total sales are 18.7% higher. Under Exp, which includes firms using intermediaries, exporters perform significantly worse in the domestic market. The last column compares pure processing trade firms with other exporters. Despite no significant difference in employment or wages, processing trade firms earn less revenue and use less capital. These patterns suggest that exporters and non-exporters face systematically different demand conditions, calling into question the use of a common domestic price deflator. Whether exporters are truly more efficient in physical terms requires the productivity estimates developed in the preceding sections.

5.3 Productivity estimates and distributions

I now turn to the productivity estimates implied by the parameters reported above. As Bernard et al. (2003) note, revenue-based productivity measures perform well only if markups are positively correlated with physical productivity. In my estimates, markups are measured by the inverse of the demand elasticity in each region (η^d), and are not clearly ranked across regions, making the relationship between markups and true efficiency ambiguous. I compute the physical productivity residual by plugging the production function and demand parameter estimates from Tables 6 and 7 into the following equation:

$$\hat{\omega_{it}} = (\hat{\phi_t} - \hat{\beta}_l l_{it} - \hat{\beta_m} m_{it} - \hat{\beta}_k k_{it} - \sum_d \hat{\beta}^d q_t^d - \hat{\tau} q r_{it} - \hat{\delta}_g D_{ig} - \hat{\delta}_t D_{it}) / (\sum_{d_i} \frac{\hat{\eta^d} - 1}{\hat{\eta^d}})$$

The revenue-based productivity measure is computed using the Stata package `prodest` with the standard specification:

$$\hat{\omega_{it}^{st}} = \hat{\phi_t^{st}} - \hat{\beta_l^{st}} l_{it} - \hat{\beta_m^{st}} m_{it} - \hat{\beta_k^{st}} k_{it}$$

I set parameters to zero when the 90% bootstrapped confidence interval contains zero. Because the physical productivity estimates incorporate destination-level effects, they are not directly comparable in levels to the revenue-based estimates. However, comparing the productivity *distributions* across firm types within each measure remains informative.

Figure 7 presents the productivity distributions under the two measures. The top panel uses revenue-based TFP with a common domestic price deflator; the bottom panel additionally controls for price effects. I distinguish three groups: direct exporters (matched in the customs dataset, indicating they establish their own foreign buyer relationships), intermediary exporters (using trading companies), and domestic-only firms. Under the common deflator, the productivity distributions of exporters and non-exporters are nearly indistinguishable. After controlling for price effects, however, the exporter distribution shifts rightward and becomes more dispersed. Two implications follow. First, exporters have, on average, higher physical productivity than non-exporters, consistent with the Melitz (2003) prediction. Second, there is meaningful overlap between the two distributions, suggesting that not all exporters are more productive than all non-exporters, a pattern potentially explained by the presence of processing trade firms.

To investigate the role of processing trade, I split exporters into pure processing trade firms and other exporters in Figure 8. Since pure processing trade firms cannot sell domestically, this classification is based on whether firms have any domestic sales. Under the physical measure, the productivity distribution of pure processing trade firms is more dispersed and shifted leftward relative to other exporters. This is consistent with the finding of Yu (2015) that low-productivity firms self-select into processing trade. Despite serving similar foreign destinations as other exporters, processing trade firms are less productive on average, a difference that the revenue-based measure fails to detect because price effects in export markets inflate their measured performance.

As a robustness check, I plot the productivity distributions separately by year and by intermediary status. The patterns are stable across years: direct exporters have higher productivity than intermediary exporters, who in turn are more productive than domestic-only firms. Details can be found in Appendix C.2.

I next examine aggregate productivity dynamics. Figures 3 and 4 show that firms faced a less protected global environment through 2005. Figure 9 compares the industry-level TFP distribution across three representative years. Under the revenue-based measure, there is a noticeable rightward shift over time. However, since aggregate demand rose in all regions over this period (Figure 6), the apparent productivity gains may partly reflect demand effects. After controlling for these effects, the industry-level TFP distributions are very similar across years.

To formalize this comparison, I follow Olley and Pakes (1996) and compute a weighted industry-level productivity measure using firms' employment shares

s_{it}:

$$\omega_t = \sum s_{it} \omega_{it}$$

Figure 10 plots the year-on-year growth rate of weighted average TFP under both measures. The two series fluctuate and often move in opposite directions. Revenue-based TFP declines sharply in 2001–2002 and then recovers in 2004, but since aggregate demand rose in all regions over this period, this pattern likely reflects demand effects rather than genuine efficiency gains. After controlling for these effects, the physical TFP growth rate oscillates around zero with no clear upward trend. As the footwear industry opened up, the standard Melitz-type selection mechanism should allocate resources to more productive firms, raising aggregate productivity. Yet there is no evidence of such reallocation in the physical TFP measure.

The muted aggregate response is consistent with the nature of China's trade liberalization. As Brandt et al. (2021) emphasize, the processing trade regime constitutes a form of *incomplete* liberalization: processing firms already enjoy duty-free imports, so tariff reductions do not generate additional competitive pressure for them. Since processing trade firms account for a large share of exporters in the footwear industry, their insensitivity to tariff cuts dampens the aggregate reallocation effect. Moreover, Brandt et al. (2017) show that during WTO accession, productivity gains came primarily from new entrants responding to input tariff cuts rather than from reallocation among incumbents. Because my above-scale sample cannot observe the entry of small firms below the reporting threshold, any entry-driven productivity gains would not appear in the aggregate measures. The within-firm analysis in the next subsection provides a more direct test of whether tariff reduction affects productivity at the firm level.

5.4 Trade liberalization and within-firm productivity dynamics

While the aggregate analysis above is informative, the main advantage of the physical productivity measure is its ability to identify within-firm productivity responses to trade liberalization. In the footwear industry, tariff reductions were not limited to the domestic market. Exporters also faced declining protection worldwide, which may have generated additional productivity gains through learning-by-exporting.

A standard approach regresses estimated productivity on contemporaneous tariff protection:

$$\hat{\omega}_{it} = c + \lambda qr_{it} + \epsilon_{it}$$

This requires the strong assumption that protection affects prices only through productivity, which is inconsistent with the pro-competitive mechanism. Moreover, this static specification ignores the dynamic evolution of productivity and likely underestimates the total impact. I therefore estimate a polynomial specification of the productivity evolution function:

$$\Delta\omega_{it} = \alpha_0 + \alpha_1\omega_{it-1} + \alpha_2\omega_{it-1}^2 + \alpha_3 qr_{it-1} + \alpha_4 dexp_{it-1} + \alpha_5\omega_{it-1} * qr_{it-1} + \nu_{it}$$

I specify the law of motion in differences rather than levels because my productivity estimates contain destination fixed effects; for firms whose destination set is stable over the sample period, these effects cancel in $\Delta\omega_{it}$. The coefficient α_4 captures the learning-by-exporting effect. All specifications include year fixed effects.

Column 1 of Table 9 uses the revenue-based TFP measure. The persistence parameter is negative and large, and the productivity response to tariff reduction (α_3) is negative but not significant. There is no evidence of learning-by-exporting. The R^2 of 0.932 reflects near-complete mean reversion in revenue TFP, consistent with the interpretation that revenue-based measures largely capture transitory demand or price shocks rather than persistent efficiency differences.

Column 2 corrects for the price effect. The results change substantially: tariff reduction now generates a significant productivity increase, and there is significant learning by exporting. The R^2 drops to 0.085, which is typical of productivity dynamics regressions once transitory price variation is removed. The key finding is not explanatory power but the sign and significance of the tariff coefficient, which is absent from the revenue-based specification. The contrast between Columns 1 and 2 underscores that revenue-based measures conflate the price response to tariff changes with the genuine productivity response, and that failing to separate these two channels masks the within-firm efficiency gains from trade liberalization.

However, the physical productivity estimates in Column 2 contain destination fixed effects. If a firm changes its destination set over time, the measured productivity change will partly reflect changes in the composition of destination fixed effects rather than genuine efficiency gains. Column 3 addresses this directly by restricting the sample to firms that did not switch destinations during the sample period, so that the destination fixed effects cancel in the first difference. This is the preferred specification. The tariff coefficient falls to $\alpha_3 = -8.04$, which is smaller than the Column 2 estimate but remains negative and significant, confirming that the larger estimate in Column 2 is partly inflated by destination composition changes. The learning-by-exporting effect also persists.

Column 4 presents the effect for pure processing trade firms. The tariff coefficient is smaller than for the full sample. This is consistent with Yu (2015) and Brandt et al. (2021): because processing trade firms already import inputs duty-free, the input cost channel of tariff reduction is muted. What tariff cuts affect for these firms is primarily the degree of import competition on the output side, a weaker channel. Learning by exporting is present but imprecisely estimated. Column 5 drops lagged export status from the law of motion. The concern is that if past exporting raises current productivity, and current productivity raises the probability of continued exporting, then lagged export status is endogenous (Lincoln and McCallum, 2018). The tariff coefficient is virtually unchanged when export status is excluded, confirming that the tariff effect is not an artifact of this endogeneity.

Appendix C.2 explore the TFP distribution and dynamics across time. Table C.2 explores the time pattern of the tariff reduction effect. The coefficient α_3 varies over time and is larger in magnitude in 2004–2006, when tariff protection declined most sharply. Although protection exposure increased slightly in 2006 due to rising tariffs in the East Asia and Pacific region, the lagged specification means this increase would not yet affect productivity dynamics. This time-varying pattern is consistent with the protection exposure trends documented in Figures 3 and 4, and cannot be detected using the revenue-based productivity measure.

6 Conclusion

Revenue-based productivity measures are the workhorse of empirical trade, yet in multi-destination settings with heterogeneous demand they systematically confound physical efficiency with output prices. This paper shows that the confound is quantitatively consequential. Embedding a CES demand system with destination-specific elasticities in a production function framework, I estimate physical productivity for Chinese footwear firms during 2000–2006 and find that the revenue-based measure and the price-adjusted measure yield substantively different conclusions on every margin examined.

First, after purging prices, ordinary exporters have higher physical productivity than non-exporters, restoring the Melitz (2003) prediction that the revenue-based measure obscures. Second, pure processing trade firms, which account for 40–58% of exporters and over 56% of export value, have substantially lower physical productivity than other exporters, a difference entirely masked in revenue data. Third, and most strikingly, the two measures disagree on whether trade liberalization raises within-firm productivity at all. Under the physical measure, tariff reductions generate significant productivity gains, and there is significant learning by exporting. Processing trade firms benefit less, consistent with the incomplete liberalization documented by Brandt et al. (2021): these firms already enjoy duty-free imports, so tariff cuts generate little additional competitive pressure.

These findings have implications for export promotion policy. The processing trade regime successfully expanded export volume, but by inducing low-productivity firms into export markets, it appears less effective at promoting the within-firm productivity growth that tariff liberalization delivers for ordinary exporters. Revenue-based evaluations of such policies overstate the performance of processing trade firms and understate the gains from liberalization, potentially distorting policy conclusions.

Several limitations should be noted. The above-scale sampling threshold of the ASM precludes studying firm entry and exit, so any entry-driven productivity gains during WTO accession (Brandt et al., 2017) are not captured. The demand elasticities are assumed to be time-invariant within each region, and some regions contribute more identifying variation than others. Collapsing the nine-region structure into fewer groups or allowing parsimonious time variation in the elasticities are natural extensions that could improve precision without altering the identification logic.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process:

During the preparation of this work, the author used ChatGPT to improve the grammar and language of the manuscript. After using this tool, the author carefully reviewed and edited the content as needed and take full responsibility for the content of the published article.

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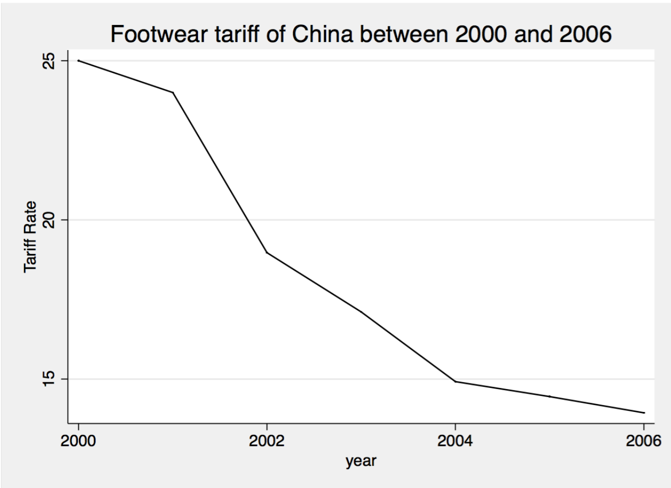
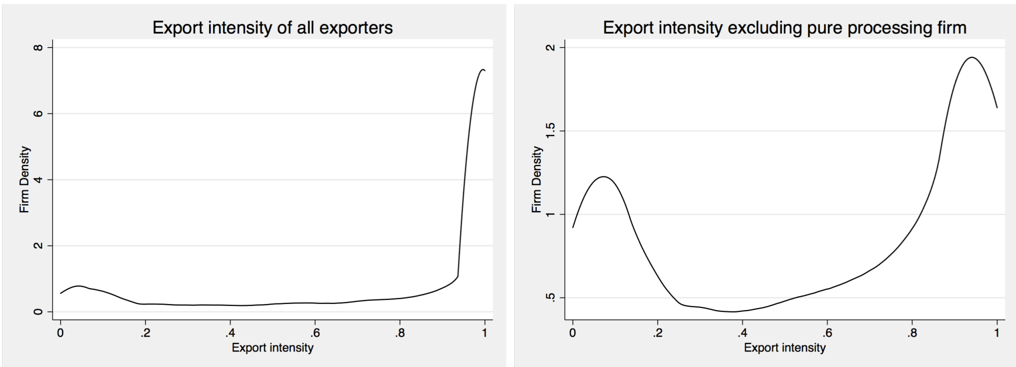
Yu, Miaojie, "Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms," *The Economic Journal*, 2015, *125* (585), 943–988.

Figure 1: Output Tariff of Footwear Industry of China



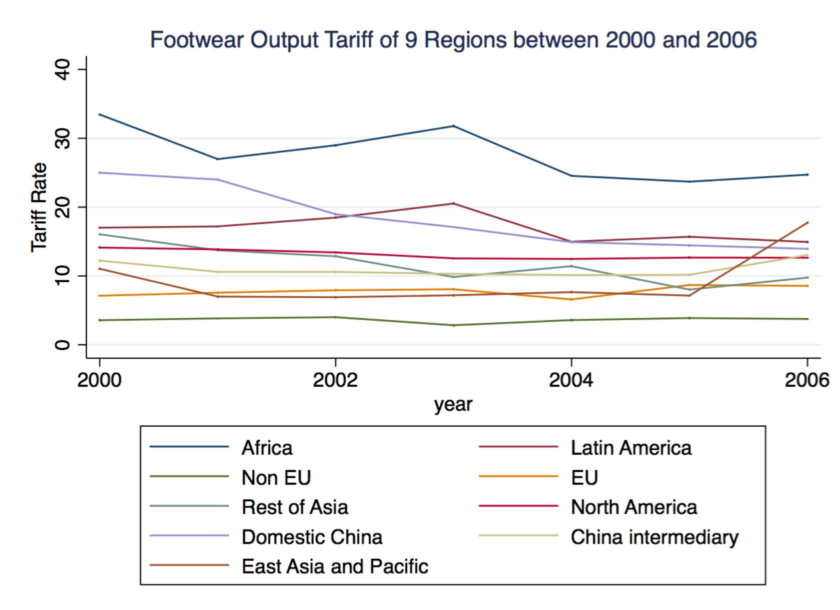
Note: The output tariff is calculated using the effectively applied tariff for the footwear industry. (HS-2 digit level with code 64)

Figure 2: Export Intensity in the Footwear Industry



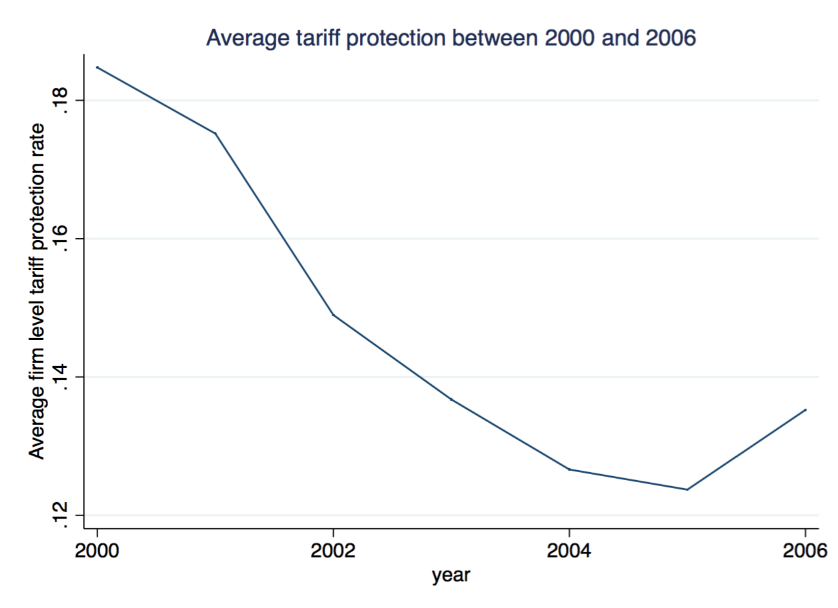
Note: Export intensity is defined as the proportion of foreign sales of exporters. Left panel includes all exporters; right panel excludes pure processing trade firms.

Figure 3: Tariff Protection in Nine Regions across Time



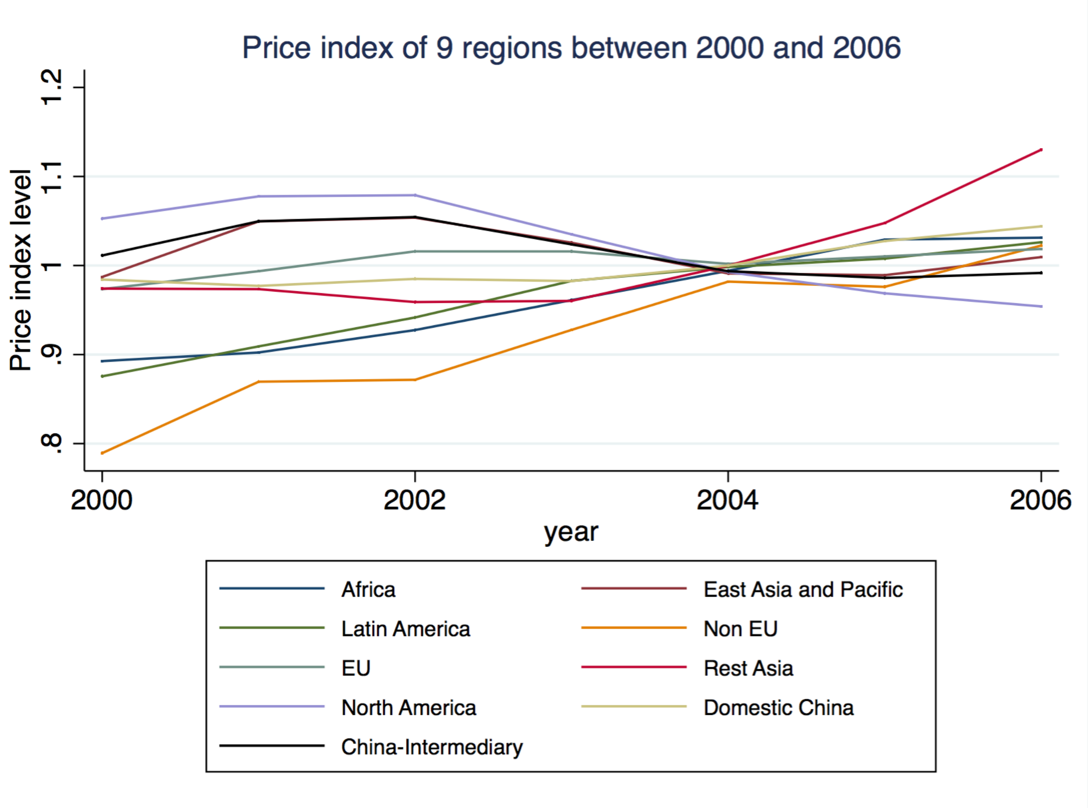
Note: Nine regions are defined in Figure A.1. The output tariff is also measured at the HS-2 digit level with code 64.

Figure 4: Firm Exposure to Tariff Protection across Time qr_{it}



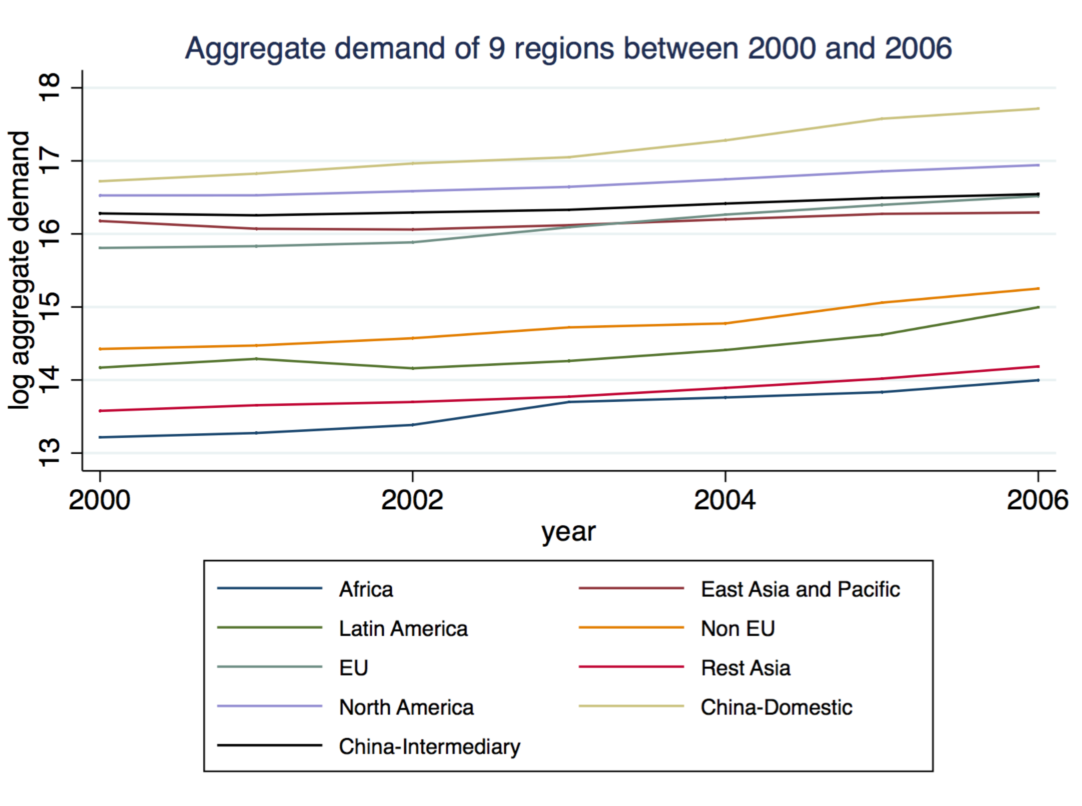
Note: The firm level tariff protection is a weighted average of regional tariff protection where the weight is sales in each region at a particular year.

Figure 5: Price Index across Time p_t^d



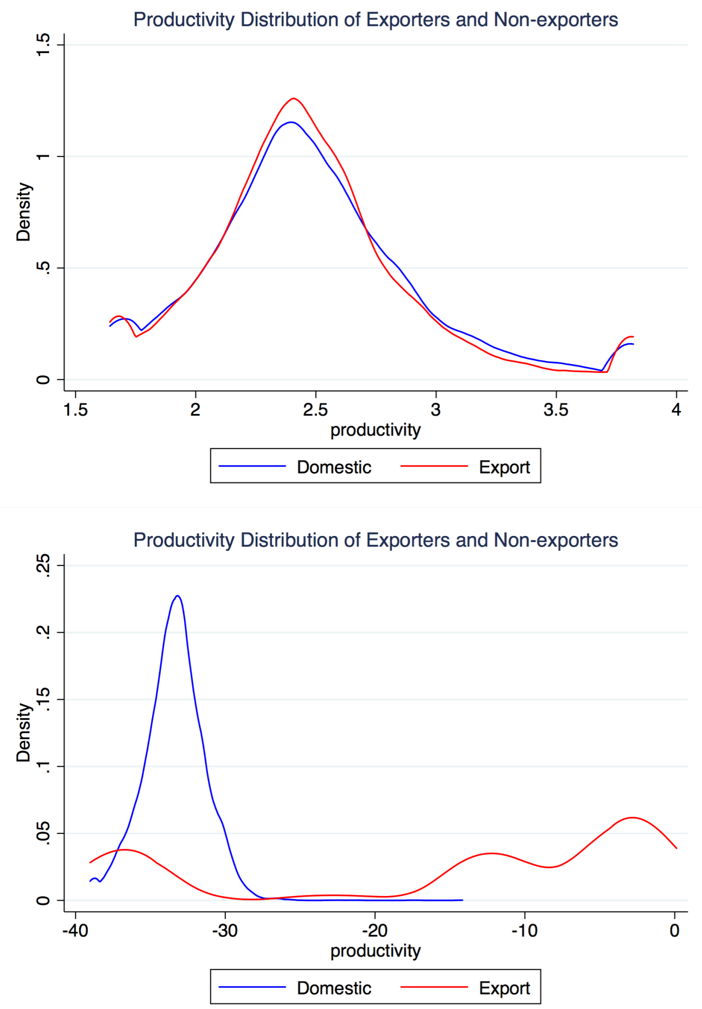
Note: Price index is an average of Import Price Index in the footwear industry of representative countries in each region. The base year in each country is 2004 and therefore the figure reflects price level compared with price level in 2004.

Figure 6: Aggregate Demand Shifter across Time q_t^d



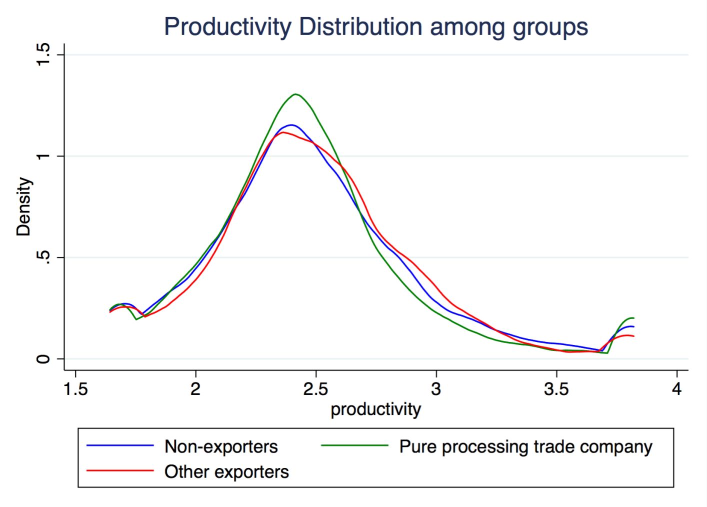
Note: The aggregate demand shifter is the deflated total import value of footwear industry in each region in each year. The unit is 1000 USD.

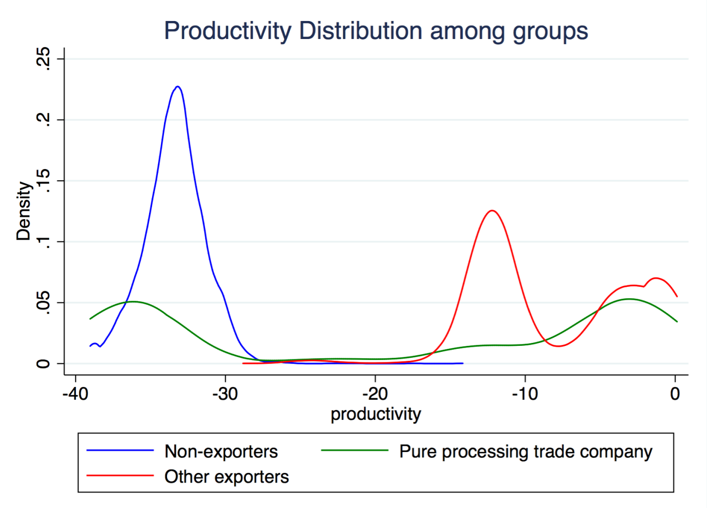
Figure 7: TFP Distribution for Exporters and Non-exporters Using Two Measures



Note: On the top is the revenue-based TFP measure using a common price deflator (output price deflator of domestic footwear market). At the bottom is the TFP distribution additionally controlling for price effects. The distribution is winsorized at the top and bottom 2.5%.

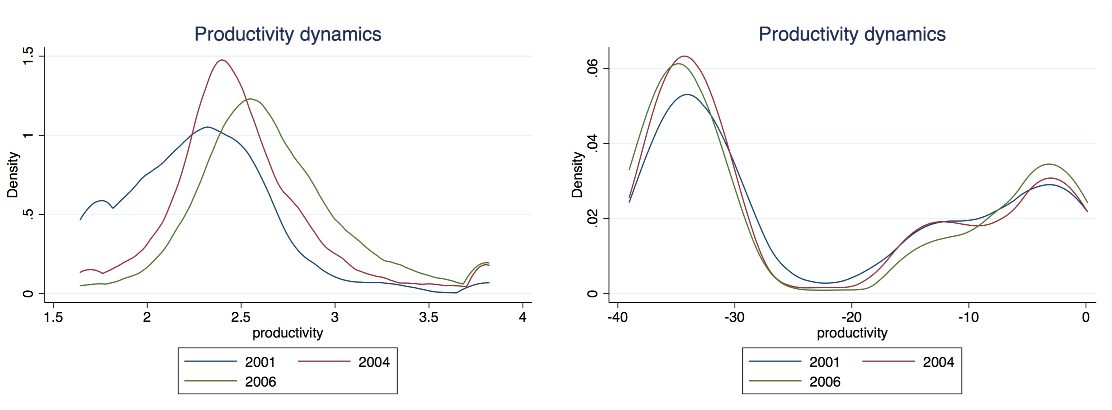
Figure 8: TFP Distributions among Groups Using Two Measures





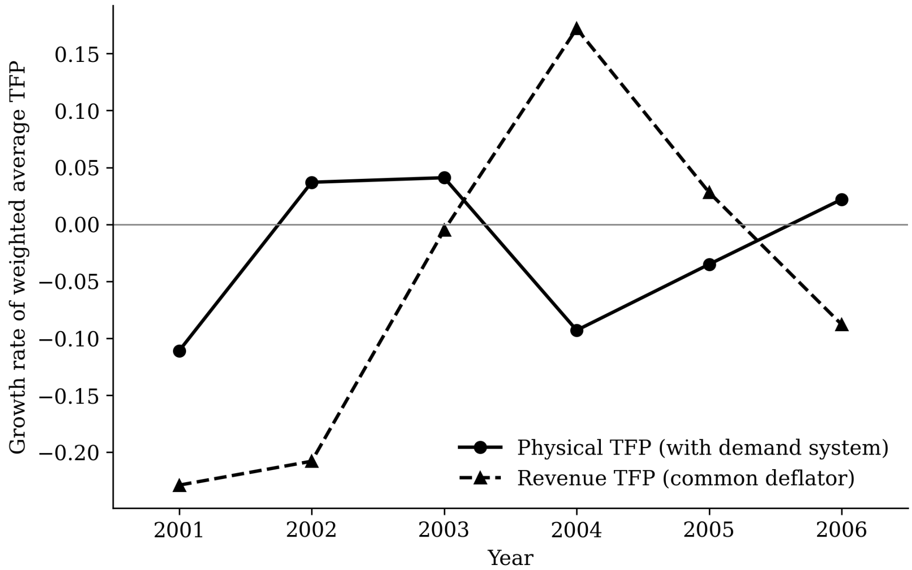
Note: On the top is the revenue-based TFP measure using a common price deflator. At the bottom is the TFP distribution additionally controlling for price effects. The distributions are winsorized at the top and bottom 2.5%.

Figure 9: Productivity Dynamics across Time Using Different Measures



Note: On the left is the revenue-based TFP measure using a common price deflator. On the right is the TFP distribution additionally controlling for price effects. The distribution is winsorized at the top and bottom 2.5%.

Figure 10: Aggregate TFP Growth Rates under Two Measures



Note: This figure plots the year-on-year growth rate of weighted average TFP, where weights are employment shares following Olley and Pakes (1996). The solid line uses the physical TFP measure from the demand system; the dashed line uses the revenue-based TFP measure with a common domestic price deflator.

Table 1: Number of Firms in the Sample and Export Rate

Year	No. of Firms	No. of Exp_d	Export Rate Exp_d	No. of Exp	Export Rate
2000	1,467	533	36.3%	930	63.4%
2001	1,877	605	32.2%	1,139	60.7%
2002	2,221	711	32.0%	1,374	61.9%
2003	1,965	668	34.0%	1,215	61.8%
2004	3,111	982	31.6%	1,866	60.0%
2005	3,499	1,092	31.2%	2,117	60.5%
2006	3,302	1,115	33.8%	2,001	60.6%

Notes: The sample covers 17,442 firm-year observations from the Annual Survey of Manufacturing (ASM), 2000–2006. Export rate is the percentage of firms exporting in a given year under each measure. Exp_d firms are directly matched to the Customs Transaction Database. Exp firms report positive export delivery value in the ASM.

Table 2: Summary Statistics

	N	Mean	SD	P25	Median	P75
Panel A: Production variables						
Revenue	17,442	52.8	171.0	9.6	18.3	42.2
Capital	17,442	11.3	46.0	1.4	3.3	8.4
Employment	17,442	519	1,162	110	205	469
Intermediate inputs	17,442	40.1	134.0	7.2	14.0	32.4
Revenue per worker	17,442	125.1	149.1	59.1	90.2	140.1
Panel B: Firm characteristics						
Firm age	17,442	9.5	8.4	5	8	11
Exporter (Exp_d)	17,442	0.33	0.47	0	0	1
Exporter (Exp)	17,442	0.50	0.50	0	1	1

Notes: The sample covers 17,442 firm-year observations from the Annual Survey of Manufacturing (ASM), 2000–2006. *Revenue* is gross output at current prices, in million RMB. *Capital* is the real capital stock, in million RMB, constructed via the perpetual inventory method of Brandt et al. (2014) using reported fixed assets, province-by-sector nominal growth rates, an investment price deflator, and a depreciation rate of $\delta = 0.09$. *Employment* is the total number of employees. *Intermediate inputs* are total intermediate inputs at current prices, in million RMB. *Revenue per worker* is revenue divided by employment, in 1,000 RMB. *Firm age* is measured in years since the firm's founding year. Exp_d equals one if the firm is directly matched to the Chinese Customs Transaction Database based on firm name and geographic information. *Exporter (Exp)* equals one if the firm reports positive export delivery value in the ASM. In the production function estimation, revenue and intermediate inputs are deflated by regional output and input price deflators constructed following Brandt et al. (2014) with base year 2004; see Section 2.2 for details.

Table 3: Share of Firms and Export Value, by Processing Status

Year	# Firms	Pure Processing	Other Exporters	Firm (%)	Export (%)
2000	930	481	449	51.7	56.7
2001	1,139	575	564	50.5	57.9
2002	1,374	685	689	49.9	56.4
2003	1,215	670	545	55.1	35.6
2004	1,866	748	1,118	40.1	60.8
2005	2,117	1,227	890	58.0	61.4
2006	2,001	1,151	805	57.5	60.9

Notes: This table reports the number and share of exporting firms by processing status. The sample includes firms with positive exports, where exports are measured by Exp. Pure processing firms are exporters that are not observed in the domestic market. Other exporters include all remaining exporting firms. Firm Share is the share of pure processing firms among all firms with positive exports in a given year. Export Share is the share of total export value accounted for by pure processing firms, computed as the total export value of pure processing firms divided by the total export value of all exporting firms in that year.

Table 4: Year-to-Year Transition Matrix of Trade Regimes

	Next-year regime		
Regime at year t	Ordinary	Mixed	Pure processing
Ordinary	92.86	7.14	0.00
Mixed	4.78	86.77	8.45
Pure processing	0.20	12.98	86.82
Total	34.32	41.36	24.32

Notes: This table reports the percentages of year-to-year transitions in firm-level trade regimes among customs-matched exporters. A firm-year is classified as Ordinary if all transactions are ordinary trade; Mixed if the firm engages in both ordinary and processing trade; and Pure processing if all transactions are processing trade. The sample includes only consecutive-year firm observations, so transitions are defined from year t to year $t+1$. Each row sums to 100.

Table 5: Destination-Market Participation of Exporting Firms

Destination market	2000	2001	2002	2003	2004	2005	2006
Region 1 – Africa	0.100	0.093	0.093	0.115	0.129	0.135	0.157
Region 2 – East Asia and Pacific	0.296	0.250	0.251	0.265	0.241	0.228	0.270
Region 3 – Latin America	0.124	0.118	0.124	0.125	0.112	0.109	0.127
Region 4 – Non-EU Europe	0.136	0.120	0.123	0.142	0.121	0.125	0.152
Region 5 – EU	0.177	0.170	0.167	0.185	0.186	0.191	0.219
Region 6 – Rest of Asia	0.121	0.108	0.110	0.138	0.135	0.130	0.144
Region 7 – North America	0.252	0.228	0.216	0.234	0.198	0.192	0.214
Region 8a – China Domestic	0.672	0.694	0.692	0.659	0.760	0.649	0.651
Region 8b – China Intermediary	0.593	0.570	0.581	0.580	0.542	0.566	0.566

Notes: Each cell reports the share of exporting firms (*Exp*) that sell to a given destination market in a given year. Because firms may serve multiple markets, shares across rows do not sum to one. The market definition used in the empirical analysis groups destinations into seven foreign regions plus two China-based markets, China Domestic and China Intermediary. Figure A.1 summarizes the market structure, and Appendix A provides the full construction details and country-to-region mapping.

Table 6: Production Function Estimates

	OLS	Proxy	Demand System
Capital	0.026	0.020	0.030
	(0.003)	(0.000)	(0.270)
Labor	0.120	0.114	0.795
	(0.009)	(0.000)	(0.200)
Material	0.845	0.839	1.020
	(0.012)	(0.000)	(0.390)
No. of observations	17,442	17,442	17,442

Notes: This table reports estimated production function coefficients under four specifications. Column (1) reports OLS estimates from a regression of deflated revenue on capital, labor, and materials, without correcting for simultaneity. Column (2) reports estimates from the ACF proxy approach using a common domestic price deflator. Column (3) incorporates the destination-specific demand system and market-level demand shifters into the estimation. Standard errors for the proxy and demand-system specifications are obtained by bootstrap with 500 replications. OLS standard errors are reported in parentheses.

Table 7: Region-Specific Demand Estimates

Parameters	$\hat{\beta}_q^d$	90% CI	Implied η^d
No. of destinations (N_{it})	10.232	[1.060, 20.870]	
Region 1 – Africa	0.624	[0.450, 0.870]	−1.601
Region 2 – East Asia and Pacific	0.129	[−0.120, 1.070]	−7.751
Region 3 – Latin America	0.809	[0.440, 1.220]	−1.236
Region 4 – Non-EU Europe	0.427	[0.000, 0.590]	−2.343
Region 5 – EU	0.626	[0.380, 0.960]	−1.599
Region 6 – Rest of Asia	0.510	[0.330, 0.940]	−1.960
Region 7 – North America	0.791	[0.020, 1.210]	−1.264
Region 8a – China Domestic	0.582	[0.320, 1.160]	−1.718
Region 8b – China Intermediary	0.615	[0.400, 1.430]	−1.627
Tariff protection (qr_{it})	−1.784	[−41.580, 93.960]	
Year FE: 2000–2001	−1.137	[−2.750, 0.060]	
Year FE: 2002–2005	0.440	[−0.530, 2.590]	
Year FE: 2006	0.546	[−1.660, 1.110]	
Textile	−0.069	[−0.820, 0.510]	
Rubber	0.083	[−1.020, 0.600]	
Plastic	−0.995	[−1.800, −0.110]	

Notes: This table reports the demand-side parameter estimates from the GMM procedure described in Section 4. $\hat{\beta}_q^d = 1/\eta^d$ is the inverse demand elasticity for each destination region. The implied elasticity is computed as $\eta^d = -1/\hat{\beta}_q^d$. Confidence intervals are obtained using 500 bootstrap replications. I report confidence intervals rather than standard errors because the bootstrap distribution need not be symmetric. Parameters whose 90% CI contains zero are set to zero in the productivity recovery.

Table 8: Characteristics Differentials for Exporters and Non-exporters

	Exp_d		Exp		Pure Processing
	All Firms	Small Firms	All Firms	Small Firms	vs. Other Exporters
Employment	0.911***	0.421***	0.741***	0.385***	−0.045
Domestic sales	0.081***	0.067	−1.559***	−1.481***	—
Total sales	0.180***	0.160***	−0.011	0.056*	−0.207***
Capital per worker	0.263***	0.329***	−0.079	−0.021	−0.353***
Average wage	0.174***	0.171***	0.100***	0.124***	0.004
Observations	17,442	13,132	17,442	13,132	10,642

Notes: Table reports β estimates from OLS regressions of log firm characteristics on export status, controlling for log employment, segment, province, and year fixed effects. Small firms have fewer than 520 employees. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Impact of Tariff Reduction on Productivity Dynamics

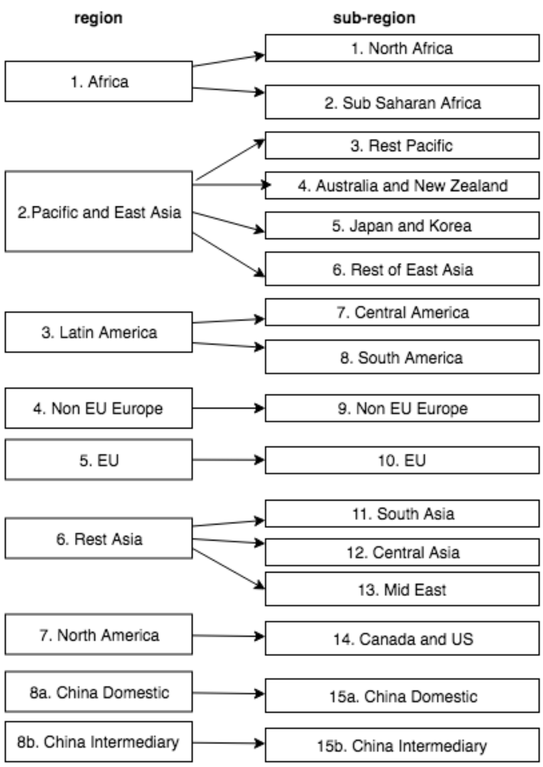
	(1) Rev TFP All firms	(2) Phy TFP All firms	(3) Phy TFP Non-switchers	(4) Phy TFP Pure processing	(5) Phy TFP No export
Dependent variable: $\Delta\omega_{it}$					
ω_{it-1} (Persistence)	-1.009***	0.308***	0.065***	0.454***	0.273***
	(0.006)	(0.037)	(0.010)	(0.073)	(0.037)
ω^2_{it-1}	-0.000	0.008***	0.001***	0.009***	0.008***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
qr_{it-1} (Protection)	-4.887	-36.981***	-8.040***	-24.655***	-37.045***
	(3.335)	(5.042)	(2.239)	(6.366)	(5.040)
$dexp_{it-1}$ (Learning)	-0.191	1.487***	0.367***	3.236***	
	(0.165)	(0.315)	(0.070)	(0.883)	
$\omega_{it-1} \times qr_{it-1}$	0.089	-1.358***	-0.326***	-2.165***	-0.941***
	(0.060)	(0.178)	(0.068)	(0.430)	(0.162)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	12,278	12,278	5,157	6,071	12,278
R^2	0.932	0.085	0.029	0.105	0.083

Notes: ω_{it} denotes physical TFP in columns (2)–(5) and revenue TFP in column (1). Column (3) restricts the sample to firms that did not switch destination regions during the sample period. Column (5) drops lagged export status from the law of motion as a robustness check for the endogeneity concern raised by the state dependence of exporting. Standard errors clustered at the firm level are reported in parentheses. Since the dependent variable uses generated regressors (estimated ω), standard OLS standard errors may be understated. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A Market definition

Here I follow Roberts et al. (2017) in defining markets and aggregate demand shifters. In the empirical analysis, destinations are grouped into nine markets, each of which is allowed to have its own demand elasticity. Within these markets, 14 subregions are defined as shown in Figure A.1. This structure can be interpreted as follows: within each region, a representative wholesaler purchases footwear products sourced from around the world.

Figure A.1: Illustrative Relationship among Regions, Subregions, and Countries



B Code: Estimation procedure

The estimation proceeds in two stages, following the control-function approach extended to incorporate the demand system.

First stage. I estimate a third-order polynomial of the revenue function in all observable right-hand-side variables: capital k_{it}, labor l_{it}, materials m_{it}, the number of active destinations n_{it}, tariff protection qr_{it}, the region-specific aggregate demand shifters $\{q_t^d\}$, and the segment and year fixed effects. This yields the predicted value $\hat{\phi}_t$, which separates the sum of unobserved productivity and observable demand components from the idiosyncratic error. Following Ackerberg et al. (2015), no production function coefficients are identified at this stage; only the composite $\hat{\phi}_t$ is recovered. For the revenue-based benchmark (without the demand system), I use the Stata package `prodest`, which implements the Levinsohn and Petrin (2003) proxy approach with the Ackerberg et al. (2015) correction.

Second stage. The second stage estimates the production function coefficients $(\beta_l, \beta_m, \beta_k)$, the nine destination-specific demand coefficients $(\beta_q^d = 1/\eta^d)$, the number-of-destinations coefficient (β_n), the tariff coefficient (τ), and the segment and year fixed effects (δ_g, δ_t) as free parameters—20 parameters in total. For a given candidate parameter vector $\boldsymbol{\beta}$, I recover productivity as:

$$\omega_{it} = \hat{\phi}_t - \beta_n\, n_{it} - \beta_l\, l_{it} - \beta_m\, m_{it} - \beta_k\, k_{it} - \textstyle\sum_d \beta_q^d\, q_t^d - \tau\, qr_{it} - \delta_g - \delta_t.$$

I then approximate the law of motion $\omega_{it} = g(\omega_{it-1}, qr_{it-1}, dexp2_{it-1}) + \nu_{it}$ by projecting ω_{it} onto a second-order polynomial in ω_{it-1}, qr_{it-1}, $dexp2_{it-1}$, ω_{it-1}^2, and $\omega_{it-1} \times qr_{it-1}$. The residual from this projection is the productivity innovation ν_{it}.

The GMM objective function minimizes:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \left(\frac{1}{N} \sum_i \mathbf{Z}_i'\, \nu_{it} \right)' \mathbf{W} \left(\frac{1}{N} \sum_i \mathbf{Z}_i'\, \nu_{it} \right),$$

where $\mathbf{Z}_i = (k_{it}, l_{it-1}, m_{it-1}, q_{t-1}^d, qr_{it})$ is the instrument matrix and $\mathbf{W} = (\mathbf{Z}'\mathbf{Z}/N)^{-1}$ is the weighting matrix. Capital enters contemporaneously because it is predetermined (decided at $t-1$); lagged flexible inputs and lagged demand shifters are orthogonal to the current innovation by the timing assumptions. The contemporaneous tariff measure qr_{it} serves as an instrument because no individual firm can influence regional tariff rates.

I solve the optimization problem using the Nelder–Mead algorithm implemented in Julia, starting from OLS initial values. The time fixed effects are initialized at zero to avoid sensitivity to starting values, following the observation that the aggregate demand shifters already absorb much of the common time variation. I obtain confidence intervals by bootstrapping the entire procedure 500 times. I report 90% bootstrapped confidence intervals rather than standard errors because the bootstrap distribution of the GMM estimates need not be symmetric. Parameters whose 90% confidence interval contains zero are set to zero in the productivity recovery.

Computational constraints. Ideally, the second-stage GMM would include destination fixed effects at the subregion or country level to absorb demand heterogeneity within regions. In practice, this would require estimating over 130 free parameters in a nonlinear GMM, which is computationally infeasible. I therefore control for destination effects only at the region level through the first-stage polynomial: these effects are absorbed into $\hat{\phi}_t$ but not separately estimated as GMM parameters. The recovered ω_{it} consequently retains unabsorbed destination-specific demand variation, making cross-firm productivity levels not directly comparable. However, for firms with stable destination sets, these effects cancel in the productivity innovation ν_{it}, so within-firm productivity dynamics—the main object of interest—remain cleanly identified.

C Additional Empirical Results and Findings

C.1 Differentials for exporters and non-exporters by year

The following two tables present the difference between exporters and non-exporters in different years by using an OLS regression and Exp as a measure of export status for each year. Across all years, exporting firms hire more workers, pay higher wages, and their performance are sometimes better in total sales.

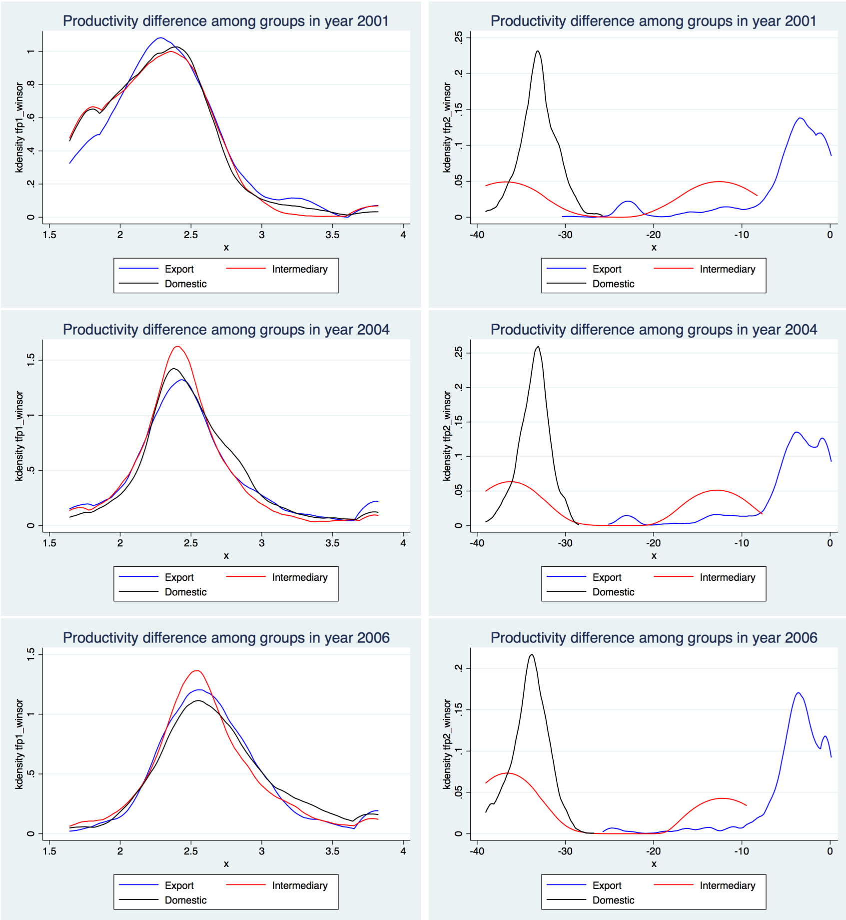
$$x_{it} = \alpha + \beta exp_{it} + \gamma l_{it} + \sum_{s} \delta_s D_s + \sum_{p} \delta_p D_p + \epsilon_{it}$$

Table C.1: Exporter Premia by Year

Year	Employee	Domestic sales	Total sales	Capital p/w	Average wage	No. of firms
Panel A: All Firms						
2000	0.880***	-1.465***	0.150**	-0.050	0.184***	1,467
2001	0.812***	-1.510***	0.084	0.074	0.146***	1,877
2002	0.745***	-1.476***	-0.011	-0.062	0.137***	2,221
2003	0.862***	-1.631***	-0.058	-0.136**	0.148***	1,965
2004	0.690***	-2.105***	-0.052	-0.113	0.056***	3,111
2005	0.733***	-1.367***	-0.032	-0.115	0.051*	3,499
2006	0.673***	-1.326***	-0.070	-0.113	0.057**	3,302
Panel B: Small Firms						
2000	0.464***	-1.430***	0.243***	0.023	0.225***	1,035
2001	0.467***	-1.447***	0.167**	0.138*	0.194***	1,388
2002	0.406***	-1.444***	0.024	0.002	0.142***	1,677
2003	0.421***	-1.476***	0.021	-0.086	0.202***	1,430
2004	0.335***	-2.001***	-0.001	-0.091	0.077***	2,428
2005	0.384***	-1.306***	0.046**	-0.043	0.065**	2,692
2006	0.354***	-1.238***	0.012	-0.056	0.075***	2,482

Notes: This table reports exporter premia by year. Each coefficient is the estimated difference between exporters and non-exporters from year-specific regressions. Panel A uses the full sample of firms, while Panel B restricts the sample to small firms. The final column reports the number of firms used in each year's regression. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure C.2: TFP distribution using different measure at different time



C.2 TFP distribution across time

I further plot the distribution across years.

Table C.2: Impact of Tariff Reduction on Productivity Dynamics, by Year

	2001	2002	2003	2004	2005	2006
α_1 (Persistence)	0.338**	0.200	0.179	−0.182	0.801***	0.106
	(0.171)	(0.134)	(0.188)	(0.183)	(0.186)	(0.220)
α_2 (ω^2_{t-1})	0.010***	0.010***	0.012***	0.001	0.002	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
α_3 (Protection)	−31.24***	−11.22	−21.36	−42.67***	−54.26***	−46.47***
	(11.71)	(9.109)	(15.26)	(14.77)	(16.70)	(17.70)
α_4 (Learning)	2.397	−1.293	−5.460*	0.049	7.660***	−2.028
	(3.047)	(2.823)	(3.277)	(3.153)	(1.972)	(2.464)
Observations	1,332	1,703	1,502	1,583	2,917	3,241

Notes: Standard errors clustered at the firm level in parentheses. Physical TFP measure used throughout. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.