Online Appendix: Input Prices, Productivity and Trade Dynamics: Long-run Effects of Liberalization on Chinese Paint Manufacturers

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C Additional Institutional Details

C.1 Trade Types in Chinese Manufacturing

This appendix summarizes the definition and shares of different trade types in the Chinese paint Industry. There are three major types of international trade in this industry.

Ordinary trade

In ordinary trade, firms purchase inputs either from domestic or foreign markets freely and have full control of the production and selling decisions. They can choose price and quantity to maximize their profits, facing the demand function.

Processing trade with imported material

In processing export with imported material, firms still maximize profits by choosing inputs and outputs freely. Under processing trade with imported inputs, the domestic firm transacts with a foreign entity, pays an import tariff, but may apply for a tariff rebate if the resulting output is exported (the foreign entities need not be the same to qualify for the rebate). As such, the firm relationships under processing trade with imported intermediates is much more similar to ordinary trade than processing trade with assembly.

Processing trade with assembly

Under processing trade with assembly, a foreign entity provides inputs to the domestic firm which must re-export its output to that firm. There is no transaction of inputs or outputs between the producer and foreign supplier(s). The producer has no control over what material inputs to be used in the production, nor how much to produce. The producer charges a fee for producing the products.

In this article, we define a firm as engaged in trade if and only if the trade is "ordinary" trade or "processing trade with imported materials", not "processing trade with assembly". In the Chinese paint industry, ordinary trade and processing trade with imported material account for about 98.8% of the total export revenue and 97.9% of import expenditure. Processing trade with assembly together with other trade types accounts for only 1.2% of export revenue and 2.1% of import expenditure.

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C.2 Chinese Paint Manufacturing Process

Paint manufacturing is typically divided into four basic steps:

- Step 1: Premixing. The pigment, resin, solvents, and additives are weighed and premixed to produce a mill base (or paste) in a mixer.
- Step 2: Milling and dispersing. The mill base is then sent to a sand mill (for most industrial and some consumer paints) or a high-speed dispersion tank (for most water-based latex paints) to grind the pigment particles and disperse them throughout the mixture. The mixture is then filtered to remove the sand particles if using a sand mill. In addition, the color phase is adjusted with color materials in this stage.
- Step 3: Thinning. The paste is thinned to produce the final product and transferred to large tanks. It is agitated with the proper amount of solvent for the type of paint desired.
- Step 4: Filtering and Packaging. The finished paint product is then packed into a container, labelled and prepared for shipment.

There is substantial scope for substitution among inputs in the production process. Poorly mixed batches of paint are unsuitable for sale, so inadequate equipment or labor can produce waste. Conversely, advanced equipment can also save material and labor. For example, a high-speed mixer can mix the inputs very well in a short period of time, so a small amount of pigment can produce a good color phase, reducing the usage of (usually expensive) pigments.

Firms typically produce a homogeneous product. Within exporters, the median export share of the largest 6-digit Harmonized System (HS) category is 93 percent, which supports our decision to model paint manufacturers as single-product firms.¹ However, the quality of the product can vary substantially across firms. Paint quality can vary across several dimensions including density, fineness of grind, dispersion, viscosity, scrub-ability, bleed resistance, adhesion, rate of drying, texture, and color. Poor quality of paint can cause peeling, chalking, and cracking, which reduce the lifespan and durability of the paint.

D Return to Scale

We assume a constant return to scale in the production function in the article. This section discusses why this is a reasonable assumption in our context. First, we use a simplified single market model to explain that demand elasticity and return to scale are not separately identified when only revenue is observed and in that sense assuming a constant return to scale is a normalization. Second, we use a two-market model to explore the conditions under which demand elasticity and return to scale can be separately identified and estimated. Finally, we conduct exercises to show that our main results regarding the import tariff liberalization are robust to a wide range of returns to scale assumptions.

D.1 Intuition of normalization: a single-market case

We consider a single market version of the static model in our article to provide intuition on why the demand elasticity and the return to scale are not separately identified when only revenue is observed. Nonetheless, the non-identification does not affect the estimation of productivity and input prices or the period profit. In this sense, assuming a constant return to scale is a normalization. The details are articulated as follows.

Consider a single market. Let the inverse demand function be:

$$P_{jt} = P_t \left(\frac{Q_{jt}}{Q_t}\right)^{1/\eta} \Phi_{jt}^{\frac{1+\eta}{\eta}},\tag{D.1}$$

where Φ_{jt} is the firm-specific demand shifter. Extending (2) and (3) in the article, we explicitly include the aggregate price (P_t) and quantity (Q_t) indices in (D.1) to show that, although De Loecker (2011) uses their

 $^{^{1}}$ Unfortunately, we do not have product-level data on domestic sales. However, we would expect that non-exporting firms are less likely to be multi-product firms compared with exporters. The lower quartile of the largest export share still derives 70 percent of total export revenue from a single product.

variation to help identify the demand elasticity, they are not useful in our estimation procedure. The reason is that our estimation approach uses the first order conditions to proxy the unobserved productivity and input prices, and P_t and Q_t are canceled out when we make the substitution. Details are provided below.

Given the demand function, the revenue function is $R_{jt} = P_{jt}Q_{jt} = \frac{P_t}{Q_t^{\frac{1}{\eta}}} \left(\tilde{Q}_{jt}\right)^{\frac{1+\eta}{\eta}}$, where $\tilde{Q}_{jt} = \Phi_{jt}Q_{jt}$ is the quality-inclusive output. The production function is the same as that in the main model:

$$Q_{jt} = A_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma} \right]^{\frac{\rho}{\gamma}}, \qquad (D.2)$$

where ρ is the parameter governing the return to scale. Similar to the main model, the quality-inclusive production function is $\tilde{Q}_{jt} = \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma} \right]^{\frac{\rho}{\gamma}}$, where the quality-inclusive productivity is similarly defined as $\tilde{\Omega}_{jt} = A_{jt} \Phi_{jt}$.

The firm's static profit maximization problem is (subject to the demand and production functions):

$$\max_{L_{jt},M_{jt},\tilde{Q}_{jt}} \qquad R_{jt} - P_{L_{jt}}L_{jt} - \tilde{P}_{Mjt}M_{jt}.$$
(D.3)
Subject to:
$$R_{jt} = \frac{P_t}{Q_t^{\frac{1}{\eta}}} \left(\tilde{Q}_{jt}\right)^{\frac{1+\eta}{\eta}}$$
$$\tilde{Q}_{jt} = \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma}\right]^{\frac{\rho}{\gamma}}$$

The first-order conditions with respect to L_{jt} , M_{jt} are:

$$\frac{1+\eta}{\eta} \frac{\partial \tilde{Q}_{jt}}{\partial L_{jt}} \frac{\tilde{Q}_{jt}^{1/\eta} P_t}{Q_t^{1/\eta}} = P_{L_{jt}},\tag{D.4}$$

$$\frac{1+\eta}{\eta} \frac{\partial \tilde{Q}_{jt}}{\partial M_{jt}} \frac{\tilde{Q}_{jt}^{1/\eta} P_t}{Q_{\star}^{1/\eta}} = \tilde{P}_{M_{jt}}.$$
(D.5)

Taking the ratio with respective to both sides of the equations and noting that $E_{L_{jt}} = P_{L_{jt}}L_{jt}$ and $E_{M_{jt}} = \tilde{P}_{M_{jt}}M_{jt}$, we can solve for material quantity:

$$M_{jt} = \left[\frac{\alpha_L E_{M_{jt}}}{\alpha_M E_{L_{jt}}}\right]^{\frac{1}{\gamma}} L_{jt}.$$
 (D.6)

Note that physical quantity M_{jt} and thus its price $\tilde{P}_{jt} = E_{Mjt}/M_{jt}$ does not depend on demand elasticity nor return to scale. This is because both demand elasticity and return to scale affect the production in a Hicks' neutral way in the CES function setup, whereas the identification of \tilde{P}_{jt} is based on the non-Hicks' neutral feature of material prices.

The labor return to the quality-inclusive output quantity is:

$$\frac{\partial \hat{Q}_{jt}}{\partial L_{jt}} = \rho \alpha_L L_{jt}^{\gamma - 1} \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma} \right]^{\frac{\rho}{\gamma} - 1}.$$
(D.7)

Plug (17) and (D.7) into (D.4), use $E_{L_{jt}} = P_{L_{jt}}L_{jt}$, we have an expression regarding $\hat{\Omega}_{jt}$:

$$\tilde{\Omega}_{jt}^{-\frac{1+\eta}{\eta}} = \alpha_L \frac{(1+\eta)\rho}{\eta} \frac{P_t}{Q_t^{1/\eta}} \frac{L_{jt}^{\gamma}}{E_{L_{jt}}} \left[\alpha_L \left(\frac{E_{L_{jt}} + E_{M_{jt}}}{E_{L_{jt}}} \right) L_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma} \right]^{\frac{1}{\eta} \frac{(1+\eta)\rho}{\eta} - 1}.$$
(D.8)

Now plug (17), (D.8), and the demand function into the revenue function $R_{jt} = P_{jt}Q_{jt}$, we have:

$$\frac{(1+\eta)\rho}{\eta}R_{jt} = \left[E_{M_{jt}} + E_{L_{jt}}\left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^{\gamma}\right)\right],\tag{D.9}$$

where R_{jt} is the predicted revenue (without any shocks or measurement errors).

Thus, given the observed revenue is with an multiplicative i.i.d. shock $\exp(u_{jt})$, the estimating equation is:

$$\ln R_{jt} = \ln \frac{\eta}{(1+\eta)\rho} + \ln \left[E_{M_{jt}} + E_{L_{jt}} \left(1 + \frac{\alpha_K}{\alpha_L} \left(\frac{K_{jt}}{L_{jt}} \right)^{\gamma} \right) \right] + u_{jt}.$$
 (D.10)

Therefore, only $\frac{\eta}{(1+\eta)\rho}$ is identified from the above equation. Note that industry-level indices P_t and Q_t do not appear in the equation to separate identify η and ρ because the first-order conditions that are used to control for productivity and input prices cancel them out.

As a result, although η and ρ are not separately identified, only their combination $\frac{\eta}{(1+\eta)\rho}$ matters for our purpose of the study. In particular, the recovering of quality inclusive material input prices does not depend on neither η or ρ . The recovering of quality inclusive productivity in (D.8) depends on ρ : the standard deviation of $\tilde{\omega} = \ln \tilde{\Omega}$ is related to ρ . If ρ is different from 1, then we can define $\tilde{\omega}' = \rho \tilde{\omega}$. Nonetheless, because $\tilde{\omega}$ is the underlying unobserved variable, setting $\rho = 1$ is a normalization for our purpose of study.

D.2 Identification and estimation in a two-market case

We now show that in a two-market setup, demand elasticity and return to scale can be separately identified in our approach if the demand elasticities of the two markets are different.

Specifically, suppose there are two markets, with similar demand functions similar to the one-market model above (and the model in our article):

$$P_{jt}^{D} = \Phi_{jt}^{\frac{1+\eta_{D}}{\eta_{D}}} (Q_{jt}^{D})^{\frac{1}{\eta_{D}}},$$
(D.11)

$$P_{jt}^{X} = \kappa \Phi_{jt} \frac{1+\eta_{X}}{\eta_{X}} (Q_{jt}^{X})^{\frac{1}{\eta_{X}}}.$$
 (D.12)

where κ capture the market size differences between the two markets and we adopt a constant κ (rather than κ_t) for ease of exposition.

Let the production function be:

$$Q_{jt} = Q_{jt}^D + Q_{jt}^X = A \left[\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma \right]^{\frac{D}{\gamma}}, \tag{D.13}$$

where ρ is the return to the scale parameter. Similar to above, the quality-inclusive production function is $\tilde{Q}_{jt} = \tilde{Q}_{jt}^D + \tilde{Q}_{jt}^X = \tilde{\Omega}_{jt} \left[\alpha_L L_{jt}^{\gamma} + \alpha_M M_{jt}^{\gamma} + \alpha_K K_{jt}^{\gamma} \right]^{\frac{\rho}{\gamma}}$, where the quality-inclusive productivity is similarly defined as $\tilde{\Omega}_{jt} = A_{jt} \Phi_{jt}$, $\tilde{Q}_{jt}^D = \tilde{\Omega}_{jt} Q_{jt}^D$, and $\tilde{Q}_{jt}^X = \tilde{\Omega}_{jt} Q_{jt}^X$. The firm's profit maximization problem is similar to (10) in our main model (and that in the single-

The firm's profit maximization problem is similar to (10) in our main model (and that in the singlemarket case above). After some similar algebra based on the first order conditions, we have the following equation:

$$\frac{(1+\eta^D)\rho}{\eta^D}R_{jt}^D + \frac{(1+\eta^X)\rho}{\eta^X}R_{jt}^X = \left[E_{M_{jt}} + E_{L_{jt}}\left(1 + \frac{\alpha_K}{\alpha_L}\left(\frac{K_{jt}}{L_{jt}}\right)^\gamma\right)\right],\tag{D.14}$$

where R_{jt}^D and R_{jt}^X are the predicted revenues of domestic sales and exports, respectively. Note that this equation is an analog to (D.9) in the one-market setup above. As a result, it alone can only identify the combinations of demand elasticities and return to scale: $\frac{(1+\eta^D)\rho}{n^D}$ and $\frac{(1+\eta^X)\rho}{n^X}$.

combinations of demand elasticities and return to scale: $\frac{(1+\eta^D)\rho}{\eta^D}$ and $\frac{(1+\eta^X)\rho}{\eta^X}$. In addition, the firm's optimal allocation of output in the domestic and export markets provides a second equation. The ratio of first-order conditions with respect to \tilde{Q}_{jt}^D and \tilde{Q}_{jt}^X suggests the following equation (a version of (22) without the error term):

$$r_{jt}^{X} = -\eta^{X} \ln \kappa + (1+\eta^{X}) \log \left(\frac{\eta^{X}}{\eta^{D}} \frac{1+\eta^{D}}{1+\eta^{X}}\right) + \frac{1+\eta^{X}}{1+\eta^{D}} r_{jt}^{D},$$
(D.15)

where r_{jt}^D and r_{jt}^X are the logarithm of R_{jt}^D and R_{jt}^X , respective. Note that the return to scale parameter does not show up in this equation. Intuitively, this is because (D.15) is obtained from the firm's optimal allocation of sales to the two markets, given the production output.

Because the production parameters $(\alpha_L, \alpha_M, \alpha_K, \gamma)$ are identified following the same logic in the article, here we focus on the identification of other parameters (in particular, the demand elasticities and the return

to scale parameter). In the rest of this subsection, we show that the return to scale is identified separately when $\eta^D \neq \eta^X$; however, it is not separately identified when $\eta^D = \eta^X$. To see this, let $\beta_1 = \frac{(1+\eta^D)\rho}{\eta^D}$, $\beta_2 = \frac{(1+\eta^X)\rho}{\eta^X}$, $\beta_3 = \frac{1+\eta^X}{1+\eta^D}$, $\beta_4 = -\eta^X \ln \kappa + (1+\eta^X) \log \left(\frac{\eta^X}{\eta^D} \frac{1+\eta^D}{1+\eta^X}\right)$. Equations (D.14) and (D.15) identify $(\beta_1, \beta_2, \beta_3, \beta_4)$. Thus, we have:

$$\eta^{D} = \frac{\beta_2}{\beta_3} \frac{1 - \beta_3}{\beta_2 - \beta_1},\tag{D.16}$$

$$\eta^X = \beta_1 \frac{1 - \beta_3}{\beta_2 - \beta_1},\tag{D.17}$$

$$\rho = \beta_1 \beta_2 \frac{1 - \beta_3}{\beta_2 - \beta_1 \beta_3},$$
 (D.18)

$$\kappa = \left[\frac{\beta_1}{\beta_2}\right]^{\frac{\beta_2 - \beta_1 \beta_3}{\beta_1 (1 - \beta_3)}} [\beta_4]^{\frac{\beta_1 - \beta_2}{\beta_1 (1 - \beta_3)}}.$$
 (D.19)

The intuition of the identification is as follows. Demand elasticities and return to scale play different roles in generating the revenues of domestic sales and exports. The return to scale influences the *level* of total output a firm can produce. The demand elasticities represent slopes of the demand function, which influence how the firm should optimally *allocate* the produced output to the two markets. When the two demand elasticities are different, the two different slopes of the demand function determines the revenue allocation to the two markets. This allocation is reflected by how the two revenues are related at the firm level. The difference in the level of revenues implied by (D.14) and the allocation of revenues implied by (D.15) provide the identification of demand elasticities and return to scale separately.

However, the above identification is conditional on $\eta^D \neq \eta^X$. If the two elasticities are the same (i.e., $\eta^D = \eta^X$), identification fails. This is because the two markets are effectively the same market if they have identical demand elasticity (i.e., the same demand slope). The optimal allocation rule will be always equally splitting the output (in logarithm) to the two markets (up to the adjustment of market sizes). As a result, it degenerates to the single-market scenario, where we discussed above that the demand elasticity and return to scale are not separately identified. Formally, if $\eta^D = \eta^X$, then by definition, this is equivalent to $\beta_3 = 1$. In this case, $\beta_2 - \beta_1 = 0$ and as a result, the system of (D.16) to (D.19) does not have a unique solution. In this case, $\rho = 1$ is a normalization as in the single-market case.

D.3 Implication for our model

In our model of the article, we have two markets. Thus, in principle, the demand elasticities and return to scale are separately identifiable, if the two markets have different demand elasticities. However, in the paint industry under consideration, the two demand elasticity estimates are insignificantly different from each other statistically. In particular, the estimate $\hat{\beta}_3 = 1.019$. According to the discussion section D.2, the demand elasticities and return to scales cannot be precisely estimated, and setting $\rho = 1$ is a normalization.

Nonetheless, we acknowledge the normalization is in an approximate sense because $\hat{\beta}_3$ is close but not exactly equal to one. We conducted a set of robustness checks to gauge the impact of such a normalization on results regarding the estimates of productivity, input prices, and trade liberalization. Specifically, we consider the return to scale parameter ρ as 0.95 1.05, and 1.1, and compute the corresponding demand elasticities respectively from the estimate of $\frac{(1+\eta^D)\rho}{\eta^D}$ and $\frac{(1+\eta^X)\rho}{\eta^X}$. As expected, the impact is minimal. For example, when setting $\rho = 1.1$, the estimate of quality inclusive

prices are identical because it does not depend on ρ or demand elasticities. Fundamental productivity is slightly different from our baseline estimate, but its correlation to our baseline estimate is 1, as shown in Table D.1. As expected, its standard deviation is exactly 1.1 (the value of ρ) times higher than that in the baseline model as shown in Table D.2. The recovered fundamental input prices and productivity are highly correlated to our baseline model estimates with correlation coefficients of 0.999 and 0.999, respectively. Their standard deviations are slightly larger than those in the baseline model, due to the same reason of larger ρ . Nonetheless, Table D.3 shows that the gap between the export and import effects on productivity are almost unchanged and, importantly, the estimated impact of liberalization of import on price is almost unchanged.

In the cases of $\rho = 0.95$ or 1.05, the results are very close to our baseline results in the article as well. Because the period profit depends on ω , p_M , P_L , K, and trade decisions, this implies the period profit is also close to the baseline results in the article.

Table D.1: Correlation coefficients of productivity and input prices estimates to the baseline estimates

ρ	0.95	1.05	1.1
$\tilde{\omega}$	1.000	1.000	1.000
\tilde{p}_M	1.000	1.000	1.000
ω	0.998	1.000	0.999
p_M	0.998	1.000	0.999

Table D.2: Standard deviations of productivity and input prices estimates

ρ	1 (baseline)	0.95	1.05	1.1
$\tilde{\omega}$	3.259	3.096	3.422	3.584
\tilde{p}_M	3.807	3.807	3.807	3.807
ω	1.031	0.934	1.108	1.173
p_M	0.192	0.188	0.193	0.193

ρ	1 (baseline)	0.95	1.05	1.1
f_0	2.344	2.026	2.646	2.945
f_e	0.087	0.077	0.093	0.098
f_i	0.264	0.240	0.280	0.295
f_{wto}	0.185	0.176	0.194	0.203
f_{ω}	0.640	0.650	0.637	0.636
g_0	0.623	0.676	0.587	0.559
g_{i0}	-0.018	-0.017	-0.018	-0.018
g_{i1}	-0.024	-0.023	-0.024	-0.024
g_{wto}	-0.020	-0.020	-0.019	-0.018
g_p	0.939	0.937	0.939	0.940

Table D.3: Estimates of quality parameters and evolution for ω and p_M

E Post-estimation Checks for Recovered Prices

This appendix section uses direct import and export prices to conduct an ex-post examination of the estimated input prices. In the data, we observe import and/or export prices (i.e., transaction-share weighted unit value) at the firm-year level, if a firm imported and/or exported in that year. The observations with import and export account for about 12 percent and 12 percent of the full sample, respectively.² The correlation between the import and export prices is 0.53 when firms both import and export, suggesting that firms that use high-quality input may also produce high-quality output, as documented in De Loecker et al. (2016).

One caveat of using such direct price data is that firms usually use a mix of both imported materials and domestically sourced materials, and we do not observe the firm-year level prices of the latter. Let's

²We have excluded imports of machinery (which counts for less than 2% in import value) and exports other than paints (which counts for less than 10% in export value). Also, we keep trade records that are in kilogram (other units count for 1.2% in trade value).

consider a simple model of price with two components: domestic price and import price. Denote P_{Mjt} as the aggregate material price index, which is an aggregation as of the two components:

$$\ddot{P}_{Mjt} = P(P_{Ijt}, P_{Djt}, s_{jt}), \tag{E.20}$$

where P_{Ijt} and P_{Djt} are the prices of imported and domestic materials, respectively, and s_{jt} represents the share of imported material to the total material. Although P_{Djt} is not observed in the data, it is likely to be positively correlated with P_{Ijt} because firms incur higher import prices (e.g., due to higher input quality requirement) may also face higher domestically sourced prices.

After recognizing this, we predict that the association between the import prices P_{Ijt} and recovered \tilde{P}_{Mjt} is positive. Table E.4 shows a set of regressions that support this prediction. Across columns (1) - (2), we find that the coefficient of the import price in logarithm is robustly positive, no matter the share of import is controlled or not. In column (3), we further control for the interaction of the import price and import share. The coefficient of the import price in the logarithm remains positive. Overall, the results show that a positive association between the import prices P_{Ijt} and recovered \tilde{P}_{Mjt} over all possible range of import shares between 0 and 1. Of course, this positive association may be also caused by the positive correlation between the import price and domestic sourced price (P_{Djt}) which is missed in the regression. Nonetheless, if this is the case, then the results suggest that the recovered material prices are reasonably associated with actual import prices and/or domestic sourced prices.

Table E.4: Estimated Quality-inclusive Prices and Import Prices

	(1)	(2)	(3)
	$\log(ilde{P}_M)$	$\log(ilde{P}_M)$	$\log(\tilde{P}_M)$
Log Import Price	0.693^{***}	0.695^{***}	0.755^{***}
	(0.145)	(0.145)	(0.218)
Import Share		-0.077	-0.987
		(0.485)	(2.505)
Log Import Price * Import Share			-0.234
			(0.631)
Observations	851	851	851
Adjusted R^2	0.025	0.024	0.023

Standard errors in parentheses.

* p < .10, ** p < .05, *** p < .01

In addition, we show the pricing menu assumption is supported by the direct trade price data. The assumption suggests that the quality-inclusive input price \tilde{P}_M depends on quality and a fundamental input price index: $\tilde{P}_M = P_M H^{\phi}$. We find that our estimated quality index h ($h = \log H$) is positively correlated with the export price – a linear regression of h on export price in logarithm, $\log(P_{Xjt})$, has a coefficient of 0.61. This is consistent with the finding in De Loecker et al. (2016), who point out that firms that use high-quality input produce high-quality output (and thus higher output prices). Using the export price as a proxy of input quality, we project the estimated quality-inclusive price against the estimated fundamental input price. We find: $\log(\tilde{P}_{Mjt}) = 1.3 \log(P_{Mjt}) + 0.7 \log(P_{Xjt})$, with both coefficient significant statistically at 1% level, which is consistent with the the pricing menu assumption.

F Additional Tables

This appendix provides additional tables. First, Table F.5 presents the estimates of κ_t and η_X when κ_t is allowed to differ over years.

Second, Table F.6 shows the transition matrix of capital stock. It reflects a strong persistence of capital transition.

Table F.5: Estimate of κ_t and η_X

	κ_{2000}	κ_{2001}	κ_{2002}	κ_{2003}	κ_{2004}	κ_{2005}	κ_{2006}	η_X
estimate s.e.	$0.797 \\ (0.185)$	$0.893 \\ (0.231)$	$0.909 \\ (0.222)$	$0.836 \\ (0.197)$	$0.872 \\ (0.218)$	0.844 (0.204)	$0.715 \\ (0.276)$	-6.946 (1.047)

Note: The p-value of of $\kappa_t = \kappa$ is 0.417.

Table F.6: Estimate of transition matrix of capital

Pre-WTO	k_1	k_2	k_3	k_4	k_5
k_1	0.733	0.201	0.056	0.011	0.000
	(0.035)	(0.031)	(0.016)	(0.008)	(0.000)
k_2	0.110	0.645	0.179	0.052	0.014
	(0.021)	(0.030)	(0.025)	(0.013)	(0.008)
k_3	0.039	0.117	0.723	0.108	0.013
	(0.012)	(0.021)	(0.030)	(0.019)	(0.008)
k_4	0.004	0.026	0.087	0.804	0.079
	(0.004)	(0.011)	(0.019)	(0.027)	(0.019)
k_5	0.006	0.007	0.007	0.070	0.910
	(0, 004)	(0.005)	(0.005)	(0.016)	(0.018)
	(0.004)	(0.000)	(0.000)	(0.010)	(0.010)
Post-WTO	$\frac{(0.004)}{k_1}$	$\frac{(0.005)}{k_2}$	$\frac{(0.005)}{k_3}$	$\frac{(0.010)}{k_4}$	$\frac{(0.010)}{k_5}$
$\overline{\frac{\mathbf{Post-WTO}}{k_1}}$	(0.004) k_1 0.743	k_2 0.184	k_3 0.045	(0.010) k_4 0.022	$\frac{k_5}{0.006}$
$\overline{\frac{\mathbf{Post}\text{-}\mathbf{WTO}}{k_1}}$		k_2 0.184 (0.020)	k_3 0.045 (0.010)	k_4 0.022 (0.007)	k_5 0.006 (0.004)
$\hline \hline $	$ \begin{array}{r} (0.004) \\ \hline k_1 \\ 0.743 \\ (0.023) \\ 0.119 \end{array} $		$(0.000) \\ k_3 \\ 0.045 \\ (0.010) \\ 0.149$		$\begin{array}{c} k_5 \\ 0.006 \\ (0.004) \\ 0.020 \end{array}$
$\hline \hline $	$ \begin{array}{c} k_1\\ 0.743\\ (0.023)\\ 0.119\\ (0.016) \end{array} $	$ \begin{array}{c} k_2\\ 0.184\\ (0.020)\\ 0.661\\ (0.022) \end{array} $	$\begin{array}{c} k_3 \\ 0.045 \\ (0.010) \\ 0.149 \\ (0.016) \end{array}$	$ \begin{array}{c} k_4 \\ 0.022 \\ (0.007) \\ 0.052 \\ (0.010) \end{array} $	$\begin{array}{c} k_5 \\ 0.006 \\ (0.004) \\ 0.020 \\ (0.006) \end{array}$
$\hline \hline \mathbf{Post-WTO}_{k_1} \\ k_2 \\ k_3 \\ \hline \end{array}$	$\begin{array}{c} k_1 \\ 0.743 \\ (0.023) \\ 0.119 \\ (0.016) \\ 0.029 \end{array}$	$\begin{array}{c} k_2 \\ 0.184 \\ (0.020) \\ 0.661 \\ (0.022) \\ 0.154 \end{array}$	$\begin{array}{c} k_3 \\ 0.045 \\ (0.010) \\ 0.149 \\ (0.016) \\ 0.637 \end{array}$	$\begin{array}{c} k_4 \\ 0.022 \\ (0.007) \\ 0.052 \\ (0.010) \\ 0.155 \end{array}$	$\begin{array}{c} k_5 \\ 0.006 \\ (0.004) \\ 0.020 \\ (0.006) \\ 0.024 \end{array}$
$\hline \hline \mathbf{Post-WTO}_{k_1} \\ k_2 \\ k_3 \\ \hline \end{array}$	$\begin{array}{c} (0.004) \\ \hline k_1 \\ 0.743 \\ (0.023) \\ 0.119 \\ (0.016) \\ 0.029 \\ (0.008) \end{array}$	$\begin{array}{c} k_2 \\ 0.184 \\ (0.020) \\ 0.661 \\ (0.022) \\ 0.154 \\ (0.017) \end{array}$	$\begin{array}{c} k_3 \\ 0.045 \\ (0.010) \\ 0.149 \\ (0.016) \\ 0.637 \\ (0.023) \end{array}$	$\begin{array}{c} k_4 \\ 0.022 \\ (0.007) \\ 0.052 \\ (0.010) \\ 0.155 \\ (0.017) \end{array}$	$\begin{array}{c} (0.013) \\ \hline k_5 \\ 0.006 \\ (0.004) \\ 0.020 \\ (0.006) \\ 0.024 \\ (0.008) \end{array}$
$\hline \hline \mathbf{Post-WTO}_{k_1} \\ k_2 \\ k_3 \\ k_4 \\ \hline \end{matrix}$	$\begin{array}{c} (0.004)\\ \hline k_1\\ 0.743\\ (0.023)\\ 0.119\\ (0.016)\\ 0.029\\ (0.008)\\ 0.016\end{array}$	$\begin{array}{c} k_2 \\ 0.184 \\ (0.020) \\ 0.661 \\ (0.022) \\ 0.154 \\ (0.017) \\ 0.024 \end{array}$	$\begin{array}{c} k_3 \\ 0.045 \\ (0.010) \\ 0.149 \\ (0.016) \\ 0.637 \\ (0.023) \\ 0.134 \end{array}$	$\begin{array}{c} k_4\\ 0.022\\ (0.007)\\ 0.052\\ (0.010)\\ 0.155\\ (0.017)\\ 0.732\end{array}$	$\begin{array}{c} (0.013)\\ \hline k_5\\ 0.006\\ (0.004)\\ 0.020\\ (0.006)\\ 0.024\\ (0.008)\\ 0.094 \end{array}$
$\hline \hline \mathbf{Post-WTO}_{k_1} \\ k_2 \\ k_3 \\ k_4 \\ \hline \end{matrix}$	$\begin{array}{c} (0.004)\\ \hline k_1\\ 0.743\\ (0.023)\\ 0.119\\ (0.016)\\ 0.029\\ (0.008)\\ 0.016\\ (0.006) \end{array}$	$\begin{array}{c} k_2 \\ 0.184 \\ (0.020) \\ 0.661 \\ (0.022) \\ 0.154 \\ (0.017) \\ 0.024 \\ (0.006) \end{array}$	$\begin{array}{c} k_3 \\ 0.045 \\ (0.010) \\ 0.149 \\ (0.016) \\ 0.637 \\ (0.023) \\ 0.134 \\ (0.015) \end{array}$	$\begin{array}{c} \hline k_4 \\ 0.022 \\ (0.007) \\ 0.052 \\ (0.010) \\ 0.155 \\ (0.017) \\ 0.732 \\ (0.020) \end{array}$	$\begin{array}{c} (0.013)\\ \hline k_5\\ 0.006\\ (0.004)\\ 0.020\\ (0.006)\\ 0.024\\ (0.008)\\ 0.094\\ (0.013) \end{array}$
$\hline \hline \mathbf{Post-WTO}_{k_1} \\ k_2 \\ k_3 \\ k_4 \\ k_5 \\ \hline \end{array}$	$\begin{array}{c} (0.004)\\ \hline k_1\\ 0.743\\ (0.023)\\ 0.119\\ (0.016)\\ 0.029\\ (0.008)\\ 0.016\\ (0.006)\\ 0.003\\ \end{array}$	$\begin{array}{c} k_2 \\ 0.184 \\ (0.020) \\ 0.661 \\ (0.022) \\ 0.154 \\ (0.017) \\ 0.024 \\ (0.006) \\ 0.007 \end{array}$	$\begin{array}{c} k_3\\ 0.045\\ (0.010)\\ 0.149\\ (0.016)\\ 0.637\\ (0.023)\\ 0.134\\ (0.015)\\ 0.002 \end{array}$	$\begin{array}{c} k_4\\ 0.022\\ (0.007)\\ 0.052\\ (0.010)\\ 0.155\\ (0.017)\\ 0.732\\ (0.020)\\ 0.108\end{array}$	$\begin{array}{c} (0.013)\\ k_5\\ 0.006\\ (0.004)\\ 0.020\\ (0.006)\\ 0.024\\ (0.008)\\ 0.094\\ (0.013)\\ 0.879\end{array}$

Note: k_1 , k_2 , k_3 , k_4 , and k_5 represent the 10, 30, 50, 70, and 90 percentiles of the capital stock in the data, respectively. Bootstrap standard errors are in parenthesis.

Third, Table F.7 shows the comparison of conditional choice probability as the model fit. The results show that the probabilities are matched reasonably well. As expected, the transition probabilities are consistent with the estimates of trade cost parameters. For example, around 97% of non-trading firms stay as non-trading suggests a significant sunk cost of entry. Also, the probability from "Neither" to "Export Only" is higher than that from "Neither" to "Import Only' means the sunk cost of importing is higher than that of exporting. Further, the probability from "Import Only" to "Both" is larger than "Export Only" to "Both" corroborates that past importing is more useful in facilitating engagement in both activities than the effect from previous exporting experience: $\hat{\lambda}_{10,11} < \hat{\lambda}_{01,11}$. These trade cost parameters, together with the benefits from trade, determine the endogenous trade participation at the firm level. We will use them as the basic components to evaluate the multi-dimensional gains from international trade at the firm level in the long run in Section 5 in the article.

Finally, Tables F.8 and F.9 show the overall impact (over a 15-year period) of the import tariff reduction on firms categorized by productivity, input price, and trade status in the year the reduction is implemented.

Actual Data	Neither	Export Only	Import Only	Both
	0.000	0.000	0.000	0.001
Neither	0.969	0.022	0.008	0.001
Export Only	0.248	0.701	0.013	0.037
Import Only	0.127	0.016	0.730	0.127
Both	0.013	0.033	0.134	0.883
Overall	0.821	0.057	0.059	0.063
Offline CCP Predicted	Neither	Export Only	Import Only	Both
Neither	0.969	0.022	0.008	0.001
Export Only	0.242	0.702	0.006	0.049
Import Only	0.123	0.010	0.722	0.145
Both	0.012	0.030	0.129	0.829
Overall	0.817	0.056	0.062	0.064
Model Predicted	Neither	Export Only	Import Only	Both
Neither	0.972	0.020	0.008	0.001
Export Only	0.151	0.799	0.006	0.045
Import Only	0.073	0.007	0.815	0.104
Both	0.011	0.023	0.098	0.868
Overall	0.812	0.059	0.066	0.064

Table F.7: Transition probabilities: data, offline CCP predicted, and model predicted

Table F.8: Effect of WTO Accession Price-Incentive to Import by Firm Type (15 Years)

	Overall	Low ω	High ω	Low p_M	High p_M
Aggregate productivity (percent)	5.5	3.5	6.3	5.8	2.6
	(1.0)	(1.1)	(1.0)	(1.0)	(1.1)
Aggregate input price (percent)	-2.4	-1.4	-2.9	-2.7	-0.8
	(0.5)	(0.4)	(0.5)	(0.5)	(0.4)
Exporters					
Percentage points	1.7	1.4	1.9	2.3	1.1
	(0.6)	(0.6)	(0.7)	(0.7)	(0.6)
Percent	11.7	10.7	12.7	14.0	8.7
	(3.8)	(4.2)	(3.5)	(3.5)	(4.3)
Importers					
Percentage points	3.4	3.0	3.9	4.4	2.5
	(1.3)	(1.3)	(1.3)	(1.3)	(1.3)
Percent	30.7	31.6	30.0	30.3	31.3
	(6.2)	(7.1)	(5.6)	(5.5)	(7.5)
Firm value (Million USD)	2.1	1.7	2.4	2.8	1.3
	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)

Notes: The groups of firms are defined by their status in the first year of the simulation. For example, the "High ω " group is the firms with ω higher than the median in the initial year. The numbers reflect the changes compared to the counterfactual where the WTO accession effect on price is removed. Each number is calculated using the with-in-group market share in the first year as the weight within each group. Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters.

3.4) (1.1)	7.4	8.2	6.5
) (1.1)	(1, 7)		0.0
	(1.1)	(1.4)	(0.9)
4 -0.8	-2.0	-5.1	-5.5
) (0.4)	(0.6)	(0.9)	(0.9)
1.0	3.4	6.0	5.0
) (0.6)	(1.1)	(1.3)	(1.1)
7 8.7	18.9	24.7	15.5
) (4.7)	(5.4)	(3.4)	(2.2)
2.5	4.8	9.3	10.2
) (1.3)	(1.8)	(2.0)	(1.6)
7 33.4	33.9	28.5	24.5
) (8.6)	(7.8)	(4.0)	(2.7)
1.2	2.2	6.9	9.0
) (0.2)	(0,1)		(0, c)
	$\begin{array}{cccc} & 1.0 \\ & (0.6) \\ 7 & 8.7 \\ & (4.7) \\ & 2.5 \\ & (1.3) \\ 7 & 33.4 \\ & (8.6) \\ & 1.2 \\ & (2.2) \\ & (2.3)$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Table F.9: Effect of WTO Accession Price-Incentive to Import by Firm Type (15 Years)

Notes: The groups of firms are defined by their status in the first year of the simulation. The numbers reflect the changes compared to the counterfactual where the WTO accession effect on price is removed. Each number is calculated using the with-in-group market share in the first year as the weight within each group. Bootstrap standard errors in parenthesis account for statistical uncertainty due to estimation of parameters.