Is Processing Good? *

Loren Brandt† Bingjing Li‡ Peter M. Morrow§

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ABSTRACT:

This paper examines the welfare effects of processing trade. Firms engaged in processing import duty free but are not allowed to sell on the domestic market. For ordinary firms, the reverse holds: imports are subject to tariffs but these firms can sell domestically. Using a structural gravity model and focusing on China, we start by documenting empirically within-industry productivity differences between ordinary and processing production. Chinese ordinary productivity increased only slightly more than for processing from 2000 to 2007. Counterfactual policy experiments imply large welfare losses ($\approx$ 5% to 10%) for Chinese agents from not being allowed to buy processing output. There are smaller welfare gains ($<$ 1%) from the duty free status of processing imports. We also develop a new method to estimate correlation parameters for multivariate Frechét distributions with trade models that deliver multiplicative gravity equations.

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†Department of Economics, University of Toronto, (brandt@chass.utoronto.ca).

‡Department of Economics, National University of Singapore, (ecslib@nus.edu.sg).

§Department of Economics, University of Toronto, (peter.morrow@utoronto.ca).

1. Introduction

Both trade economists and development practitioners have long believed that policies encouraging integration into the global economy can expedite economic development. One common policy is export processing zones or institutions that allow firms to engage in processing. Under this regime firms import intermediate duty free circumventing tariffs. However, these firms are rarely–if ever–allowed to sell these goods to domestic firms or consumers. Firms engaged in "ordinary" trade, on the other hand, are allowed to sell domestically but are subject to tariffs on imports of capital equipment and intermediate inputs. Consequently, processing regimes potentially bring the benefits of increased labor demand but rarely allow domestic consumers of final goods or intermediate inputs to benefit from lower prices. Despite the existence of many papers analyzing processing regimes, there have been very few cost-benefit analyses.[1]

This paper conducts such an an analysis by examining the welfare implications of China's processing regime for the years 2000 through 2007.[2] We conduct this exercise using a a multi-sector, multi-country, general equilibrium model of ordinary and processing trade using methods developed by Eaton and Kortum (2002), Costinot, Donaldson and Komunjer (2012), Caliendo and Parro (2015), and Levchenko and Zhang (2016).

The paper has two goals. First, we document the trajectories of TFP for firms engaged in ordinary and processing production during the years 2000-2007. This allows us to assess whether or not states of technology differ between ordinary and processing, and whether any differences

[1] e.g. Madani (1999), for Economic Co-operation and Development (2007) offer descriptive analysis of processing in various countries but do not engage in formal cost-benefit analysis.

[2] The vast majority of Chinese exports occur through either ordinary or processing trade, which combined represent more than 95 percent of Chinese exports between 2000 and 2007. For a general discussion, see Naughton (1996). Within processing trade, there are two forms: import and assembly and pure assembly, of which the earlier represents more than 75 percent. Both forms can import duty free, but are restricted in terms of their ability to sell to the domestic market. Because of these similarities, we combine these two organizational forms into a single form that we refer to as "processing". Differences between the two, including the right to source domestically, ownership of imported intermediates, and taxation as a legal entity, are the focus of a growing literature. For a discussion of some of these differences, see Feenstra and Hanson (2005), Branstetter and Lardy (2008), and Fernandes and Tang (2012). Processing confers substantial benefits on export processors, most importantly, the right to import duty-free raw materials, components, and capital equipment used in processing activity, and preferential tax treatment (Naughton, 1996). Processing firms are not allowed to use these inputs in production for sales on the domestic market. In contrast, firms engaged in ordinary trade must pay duties on their imports, but are free to sell on the domestic market.

are essential for understanding whether allowing processing firms to sell domestically will lead to a different menu of prices for Chinese consumers. Second, we conduct a series of counterfactual experiments that assess the welfare effects of processing. The first experiment assess the welfare gains of the tariff exemption for processing by comparing the welfare associated with the observed equilibrium with one in which those firms faced the same import tariffs as firms engaged in ordinary production. The second experiment calculates welfare in an equilibrium which firms engaged in processing are counterfactually allowed to sell to domestic agents.

We emphasize three results. First, although averages are very similar, there are substantial differences in measured productivity between firms engaged in ordinary and processing across industries in a given year. Looking at the premium attached to productivity relative to ordinary production, estimates in 2000 range from -19% to +11%. This heterogeneity suggests that looking at a single premium estimated across industries may be misleading.

Second, we find that there are substantial welfare *losses* for Chinese consumers and firms associated from not being able to buy final goods and intermediate inputs from processing firms. We estimate that the real wage for a representative agent in China in 2000 would have been approximately 10% higher in a counterfactual world in which processing firms could sell to domestic agents. The increase in real income would have been smaller ($\approx 5\%$) due to a loss of tariff income as processing sales would crowd out import competition.[3] We also show that this result is not due to their simple duty-free status but rather their ability to offer different menus of prices to consumers and downstream firms.

Third, we find relatively small gains ($< 1\%$) from the existing policy that the processing sector imports duty free. This final result is consistent with small estimated effects of international trade liberalization in quantitative trade models including Eaton and Kortum (2002) and Caliendo and Parro (2015).

Our finding of relatively large gains from allowing processing firms to sell domestically comes from two aspects of our model: i) imperfectly correlated productivity draws by firms engaged in

[3] Costinot and Rodríguez-Clare (2014) obtain a similar result that real income increases by less than real wages due to (counterfactual) trade liberalization.

ordinary and processing trade, and ii) international trade costs.

First, our modelling framework allows–but does not impose–for productivity draws between ordinary and processing production within an industry to be imperfectly correlated. It is unrealistic to assume that ordinary and processing trade share the same productivity level in a given industry; it is also unrealistic to assume that productivity draws across the two forms of production are uncorrelated. For this reason, we follow Ramondo and Rodríguez-Clare (2013) and use a multivariate Frechét distribution that allows for productivity draws between the two forms to be imperfectly correlated. Despite the fact that this parameter has generally be non-identified in the literature, we combine the insights of Berry (1994) with the triad approach of Caliendo and Parro (2015) to identify this crucial parameter. It is key for our results that we find that while draws are positively correlated, the correlation is far from perfect.

Allowing processing firms to sell domestically is potentially more powerful than international trade liberalization due to the presence of large documented barriers to international trade. Because of these barriers, Chinese consumers spend relatively little on imported goods, implying that the effect of lower tariffs on the domestic price index is small. However, for domestic production, there are no such trade costs implying larger potential effects of price changes on welfare. This finding of the importance of domestic market liberalization for welfare links this paper to other papers that find large welfare effects of removing barriers to trade and migration. For example, Atkin and Donaldson (2015) find large welfare effects of within country trade barriers and Tombe and Zhu (2015) find large gains from lifting migration restrictions within China.

In terms of our framework, our framework is most closely related to Caliendo and Parro (2015) and Levchenko and Zhang (2016). We allow for multiple factors of production (capital and labor) as well as traded intermediate inputs which are essential for thinking about the quantitative implications of China's position in global value chains. However, our focus on productivity differences between ordinary and processing production requires an important extension.

Finally, by examining the welfare implications of China's processing regime, it is closely linked to a literature that assesses both the causes and consequences of this China's processing regime.

Although we focus on tariff treatment as emphasized in Brandt and Morrow (2017), our reliance on a structural model of international trade allows us to identify aggregate effects unlike the reliance on difference-in-difference results in that paper. Other papers that analyze the characteristics of firms engaged in processing relative to ordinary trade include Yu (2015), Kee and Tang (2016), Manova and Yu (2016), Dai, Maitra and Yu (2016), and Li, Smeets and Warzynski (2017).

Section 2 describes the theoretical apparatus that we bring to our question. Section 3 describes the data that we use for this exercise. Section 4 details how we map the model to the data. Section 5 presents our results including productivity differences and the results of the counterfactual simulations. Finally, section 6 concludes by summarizing our results and offering further paths for research.

2. Model

The model that we use for our quantitative exercise must possess a number of important building blocks. First, in order to conduct quantitative experiments, it must be an equilibrium model with market clearing in which all prices and quantities are endogenous. Second, because processing firms import intermediate inputs in order to produce and export goods, there must be rich input-output linkages. Third, because processing activities tend to be concentrated in certain industries (e.g. Brandt and Morrow (2017)), it must possess multiple industries. Finally, in order to distinguish productivity from differences in capital intensity, we must have both multiple factors and Ricardian productivity differences.

We now describe our model in detail. It is a multi-country, multi-sector, multi-factor general equilibrium model in which Chinese firms engage in either ordinary or processing production. As in Brandt and Morrow (2017), we model ordinary and processing trade as follows: firms engaging in processing trade do not face tariffs on imports but are restricted from selling on domestic (i.e. Chinese) markets. Ordinary firms face import tariffs but are free to sell on Chinese markets. Firms engaged in ordinary production are allowed to sell to processing firms but the reverse is not allowed. In what follows, we refer to whether a firm or industry sells or exports through ordinary or processing as the "organization of production" or the "organization of trade", respectively. We further assume that this distinction holds only for China: all firms outside China engage in ordinary trade exclusively.[4]

2.1 Preliminaries

In addition to China, there are N countries indexed i. Because our model is static, we suppress any time subscript although we re-introduce it when when we present our empirical work. As in Levchenko and Zhang (2016), there are J traded and one non-traded sectors; these sectors are indexed j and/or k. We model China as two additional markets: an ordinary market (o) and a processing market (p). Primary factors of production are fully mobile across these two markets in China. In terms of notation, there are $N+2$ "countries" indexed with subscripts $i = 1,...,N,o,p$. Assume that countries are ordered such that $i = 1,...,N$ indexes non-China countries, and the $N+1^{th}$ and the $N+2^{nd}$ represent ordinary and processing production in China, respectively. In some cases below, we use the subscript c for China such as when we are referencing the utility function of its representative consumer or factor prices that are common across the two organizational forms.

Within each (superscript) industry j, there is a continuum of varieties indexed ω^j. As in Caliendo and Parro (2015), all trade is in varieties of intermediate inputs. Each variety is sourced from its lowest cost supplier inclusive of tariffs and transport costs. In a given destination location n, these intermediates are either costlessly transformed into (non-traded) consumption goods or used as intermediate inputs for downstream production.

Each country possesses exogenous endowments of two primary factors of production: labor L_n and capital K_n. These factors are fully mobile across sectors within a country but are internationally immobile. Factor payments are w_n and r_n, respectively. Labor and capital are fully mobile across

[4]Firms engaged in processing sometimes also receive tax breaks and/or subsidized land. Because those policies are often targeted at multinationals to attract FDI in general and are not processing-specific, we only focus on these two characteristics of processing in this paper.

ordinary and processing in China such that we can write their factor returns as w_c and r_c.[5]

2.2 *Demand*

Preferences are identical and homothetic across countries with each representative consumer in a country n possessing the following utility function defined over $J+1$ consumption aggregates:

$$U_n = \Pi_{j=1}^{J+1} \left(C_n^j\right)^{\alpha^j}$$

2.3 *Production*

Potentially, any variety ω^j can be produced in any country. Production requires three factors of production (labor, capital, and a composite intermediate good) and producers differ in the efficiency of production: $z_n^j(\omega^j)$. More precisely, the production technology of variety ω^j is

$$q_n^j(\omega^j) = z_n^j(\omega^j) \left[l_n^j(\omega^j)\right]^{\gamma_{l,n}^j} \left[k_n^j(\omega^j)\right]^{\gamma_{k,n}^j} \Pi_{k=1}^{J+1} \left[m_n^{kj}(\omega^j)\right]^{\gamma_n^{kj}}$$

where $\gamma_{l,n}^j + \gamma_{k,n}^j + \sum_{k=1}^J \gamma_n^{kj} = 1$. We allow the Cobb-Douglas factor shares to vary across both industries (as is common in the literature) but also across countries within an industry. $l_n^j(\omega^j)$ and $k_n^j(\omega^j)$ are the labor and capital, respectively, associated with producing variety ω^j in country n, and $m_n^{kj}(\omega^j)$ is the amount of composite good k demanded by a producer of that variety. Unit cost is then $c_n^j / z_n^j(\omega^j)$ where

$$c_n^j \equiv \Upsilon_n^j w_i^{\gamma_{l,n}^j} r_i^{\gamma_{k,n}^j} \Pi_{k=1}^J \left[p_n^k\right]^{\gamma_n^{kj}} \tag{1}$$

and Υ_n^j is an industry specific constant.[6] p_n^k is the price of a composite unit of k in destination country n as we discuss shortly.

[5] We treat machinery and equipment as a traded intermediate good whose price differs across ordinary and processing firms due to differential tariff treatment and the (legal) restriction that processing firms cannot sell to (domestic) ordinary firms which prevents price arbitrage. For this reason, capital K is best thought of as comprising its non-traded component such as land and structures.

[6] $\Upsilon_n^j \equiv \left(\gamma_{l,n}^j\right)^{-\gamma_{l,n}^j} \left(\gamma_{k,n}^j\right)^{-\gamma_{k,n}^j} \Pi_{k=1}^J \left(\gamma_n^{kj}\right)^{-\gamma_n^{kj}}$.

As in Caliendo and Parro (2015), the composite intermediate in sector j, Q_n^j, is a CES aggregate of industry-specific varieties such that

$$Q_n^j = \left[\int x_n^j(\omega^j)^{\frac{\sigma^j - 1}{\sigma^j}} d\omega^j \right]^{\frac{\sigma^j}{\sigma^j - 1}}$$

where $x_n^j(\omega^j)$ is the *demand* for variety ω^j from the lowest cost supplier. Composite intermediate goods are used as intermediate inputs for downstream production as well as final goods in consumption. The goods market clearing condition for the composite intermediate good in sector j in country n is therefore

$$Q_n^j = C_n^j + \sum_{k=1}^{J+1} \int m_n^{jk}(\omega^k) d\omega^k.$$

For ordinary production in China, the analogous expression is

$$Q_o^j = C_c^j + \sum_{k=1}^{J+1} \int m_o^{jk}(\omega^k) d\omega^k.$$

This expression shows that all ordinary production in China is either consumed in China or is used as intermediate inputs. For processing, goods market clearing is given by $Q_p^j = \sum_{k=1}^{J} \int m_p^{jk}(\omega^k) d\omega^k$ such that all of the composite processing output must be used in the production of processing goods and none can be used to satisfy final demand.[7]

2.4 *Pricing and Transport Costs*

As in Eaton and Kortum (2002), each country has the ability to produce any variety in any industry, but the variety is only produced in that country in equilibrium if that country is the lowest cost provider of the variety in some market. Transport costs and tariffs imply that even if a given firm in a given source country is the lowest cost provider of a given variety in some destination market, it need not be the lowest cost supplier to all destination markets.

There are two components of trade costs: iceberg international trade costs and ad-valorem tariffs. Treating the earlier first, define d_{ni} as the distance between n and i, and $g^j(d_{ni})$ as a weakly increasing industry-specific function that maps distance onto iceberg trade costs. We impose that

[7] This implies that the entire non-traded sector is organized through ordinary production.

the function $g^j(d_{ni})$ is symmetric in distance such that $g^j(d_{ni}) = g^j(d_{in})$. To allow for asymmetries, as in Waugh (2010), assume that exporter i-industry j specific multiplicative iceberg costs t_i^j allow the total iceberg costs between two locations to depend on the direction in which the shipment is going.[8] $t_i^j = 1$ for domestic shipments. Finally, define ad-valorem tariffs $(1 + \tau_{ni}^j)$ where τ_{ni}^j is the statutory tariff that n imposes on good j shipped from i. All exports from China to external markets are subject to the same tariff level regardless of their organization such that $\tau_{io}^j = \tau_{ip}^j \;\; \forall i,j$. The total per-unit cost of shipping a unit of a variety of j from i to n, κ_{ni}^j, can then be expressed as

$$\kappa_{ni}^j \equiv (1 + \tau_{ni}^j) g^j(d_{ni}) t_i^j. \tag{2}$$

The equilibrium price of ω^j in country n, $p_n^j(\omega^j)$, is then the lowest price offered from all possible source countries:

$$p_n^j(\omega^j) = \min_i \left\{ \frac{c_i^j \kappa_{ni}^j}{z_i^j(\omega^j)} \right\}.$$

In addition, we follow Eaton and Kortum (2002), Waugh (2010), and Levchenko and Zhang (2016) by setting $\kappa_{nn}^j = 1 \;\; \forall n,j$.

2.5 *Productivity Distributions*

Ricardian motives for trade are introduced as in Eaton and Kortum (2002) and Costinot et al. (2012). Outside of China, firms in country i-industry j draw from Frechét distributions with location parameters λ_i^j and shape parameters θ^j. Following Eaton and Kortum (2002), we refer to λ_i^j as the *state of technology* to distinguish it from average productivity which is given by $\left(\lambda_i^j\right)^{\frac{1}{\theta^j}}$.

However, for ordinary and processing trade within a Chinese industry, this is unsatisfying. On one extreme, there is no reason to assume that draws between the two organizational forms are independent and, on the other extreme, there is no reason to think that draws are taken from the exact same distribution. For this reason, we follow Ramondo and Rodríguez-Clare (2013) by assuming correlated draws $\{z_o^j(\omega^j), z_p^j(\omega^j)\}$ for ordinary and processing production from the

[8] This can occur, for example, if there are (iceberg) congestion costs associated with full ships leaving China, and lower congestion costs associated with shipments from the US (for example). All of our empirical results are robust to restricting exporter-industry specific costs to be the same across all industries: $t_i^j = t_i \;\; \forall j$.

following multivariate Frechét distibution:

$$F^j(z_o,z_p) = exp\Big\{ - \Big[(\lambda_o^j)^{\frac{1}{1-\nu}} z_o^{-\frac{\theta^j}{1-\nu}} + (\lambda_p^j)^{\frac{1}{1-\nu}} z_p^{-\frac{\theta^j}{1-\nu}}\Big]^{1-\nu}\Big\}. \tag{3}$$

$\nu \in [0,1)$ governs the correlation between z_o and z_p. A higher value of ν increases this correlation, and $\nu = 0$ corresponds to the case where z_o and z_p are independent. Section 4 shows how we can identify ν using a triad approach that builds on Berry (1994) and Caliendo and Parro (2015). As this correlation declines ($\nu \to 0$), there is more heterogeneity in productivity across ordinary and processing, leading to more potential gains from buying from both types of firms. As the correlation increases ($\nu \to 1$), the draws are more correlated causing there to be fewer gains from buying from both types of firms relative to buying from only one.[9]

2.6 *Equilibrium Trade Shares*

We now define equilibrium expenditure shares for non-China countries, the ordinary sector of China, and the processing sector for China. For expenditure shares outside of China, define the share of total expenditures by (importing) country n in industry j accruing to (exporter) i as π_{ni}^j. When looking at sales by non-China sources into non-China destinations, the expression for π_{ni}^j is

$$\pi_{ni}^j = \frac{\lambda_i^j (c_i^j \kappa_{ni}^j)^{-\theta^j}}{\Phi_n^j}. \tag{4}$$

where

$$\Phi_n^j \equiv \left[(\lambda_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\lambda_p^j)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}}\right]^{1-\nu} + \sum_{i'=1}^{N} \lambda_{i'}^j \left(c_{i'}^j \kappa_{ni'}^j\right)^{-\theta^j}. \tag{5}$$

See Appendix A.B.1 for a proof. The treatment of expenditure shares accruing to ordinary and processing firms in China requires slightly more care. The share of expenditure on sector j goods in destination n accruing to firms engaged in ordinary trade in China is given by

$$\pi_{no}^j = \frac{(\lambda_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j\right)^{-\frac{\theta_j}{1-\nu}}}{(\lambda_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j\right)^{-\frac{\theta_j}{1-\nu}} + (\lambda_p^j)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j\right)^{-\frac{\theta_j}{1-\nu}}} \frac{\left[(\lambda_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j\right)^{-\frac{\theta_j}{1-\nu}} + (\lambda_p^j)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j\right)^{-\frac{\theta_j}{1-\nu}}\right]^{1-\nu}}{\Phi_n^j}. \tag{6}$$

[9]This is the same intuition as for why the gains from trade are declining in θ^j in Eaton and Kortum (2002).

See Appendix A.B.3 for a proof. The first fraction to the right of the equality captures the share of ordinary trade in total *Chinese* exports to destination market n. The second fraction to the right of the equality captures the share of country n expenditures that accrue to China as a whole. The first fraction is larger when λ_o^j/λ_p^j is relative higher, the relative cost of ordinary trade c_o^j/c_p^j is lower, or iceberg costs confer an advantage to ordinary trade $\kappa_{no}^j < \kappa_{np}^j$.[10] Similarly, the expenditure share accruing to processing is

$$\pi_{np}^j = \frac{(\lambda_p^j)^{\frac{1}{1-\nu}}\left(c_p^j\kappa_{np}^j\right)^{-\frac{\theta_j}{1-\nu}}}{(\lambda_o^j)^{\frac{1}{1-\nu}}\left(c_o^j\kappa_{no}^j\right)^{-\frac{\theta_j}{1-\nu}}+(\lambda_p^j)^{\frac{1}{1-\nu}}\left(c_p^j\kappa_{np}^j\right)^{-\frac{\theta_j}{1-\nu}}}\frac{\left[(\lambda_o^j)^{\frac{1}{1-\nu}}\left(c_o^j\kappa_{no}^j\right)^{-\frac{\theta_j}{1-\nu}}+(\lambda_p^j)^{\frac{1}{1-\nu}}\left(c_p^j\kappa_{np}^j\right)^{-\frac{\theta_j}{1-\nu}}\right]^{1-\nu}}{\Phi_n^j}. \tag{7}$$

Deriving import shares *into* the processing and ordinary sectors in China is straight-forward and obtained by setting $\kappa_{op}^j = \kappa_{pp}^j = \infty \ \forall \ j$. $\kappa_{op}^j = \infty$ imposes that processing firms cannot sell to firms organized into ordinary production, and $\kappa_{pp}^j = \infty$ imposes that processing firms cannot sell to themselves.[11] This allows us to derive a share of expenditure by processing firms accruing to country i as

$$\pi_{pi}^j = \frac{\lambda_i^j(c_i^j\kappa_{pi}^j)^{-\theta^j}}{\Phi_p^j}, \tag{8}$$

where Φ_p^j is given by setting $n = p$ and $\kappa_{pp} = \infty$ in equation (5). The share of expenditure by the ordinary portion of j accruing to ordinary firms o or other to countries i is given analogously:

$$\pi_{oi}^j = \frac{\lambda_i^j(c_i^j\kappa_{oi}^j)^{-\theta^j}}{\Phi_o^j} \tag{9}$$

where Φ_o^j is given by setting $n = o$ and $\kappa_{op}^j = \infty$ in equation (5). See Appendix B.2 for formal proofs for these expressions. For the non-traded sector, $\pi_{ni}^{J+1} = 1$ if $i = n$ and $\pi_{ni}^{J+1} = 0$ if $i \neq n$. Finally, as in Eaton and Kortum (2002), price distributions are give by:

$$p_n^j = A^j\left[\Phi_n^j\right]^{-\frac{1}{\theta^j}} \qquad n = 1,...,N,o,p. \tag{10}$$

[10]We abstract from the last of these three in this paper but continue to carry notation throughout for generality.

[11]We make the assumption that processing firms source from ordinary firms but not from other processing firms for two reasons. 1. Legally, processing output is required to leave the country. While there are exemptions for selling to other processing firms, we believe the volume of these sales at the industry level is very small. 2. Assuming that all processing output is exported provides a very powerful identifying assumption when breaking industry level output into ordinary and processing output which is required for our empirical strategy in section 4. See also Appendix C.

where $A^j \equiv \left[\Gamma\left(\frac{\theta^j+1-\sigma_j}{\theta^j}\right)\right]^{\frac{1}{1-\sigma_j}}$ and $\Gamma(\cdot)$ is the gamma function.

2.7 Goods Market Clearing

Total expenditure on industry j goods for non-processing be decomposed as follows for $n = 1,...,N$:

$$X_n^j = \alpha^j I_n + \sum_{k=1}^{J+1} \gamma_n^{jk} \left[\sum_{i=1}^{N+2} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k}\right]. \tag{11}$$

It is useful to describe the components of equation (11) in detail. The first component ($\alpha^j I_n$) reflects final consumption expenditure on the industry j composite good in n. For a given industry k-country i pair, the second component, $\gamma^{jk} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k}$, describes the share of country i expenditures on k that go to country n (exclusive of tariffs), multiplied by the cost share of those industry k sales accruing to upstream industry j. Summing across i gives global expenditure in industry k accruing to intermediate inputs in industry j, country n; then summing over downstream industries k captures total demand for inputs from industry j that are produced in n.

For ordinary goods in China, the expression is analogous and given by

$$X_o^j = \alpha^j I_c + \sum_{k=1}^{J+1} \gamma_o^{jk} \left[\sum_{i=1}^{N+2} X_i^k \frac{\pi_{io}^k}{1+\tau_{in}^k}\right]. \tag{12}$$

For processing in China, the expression is similar except all processing production must be used as an intermediate input for exports, and cannot be used for either domestic production or as an intermediate input for domestic final sales:

$$X_p^j = \sum_{k=1}^{J+1} \gamma_p^{jk} \sum_{i=1}^{N} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k}. \tag{13}$$

Income is easily defined as $I_n \equiv w_n L_n + r_n K_n + R_n$ where R_n is the value of tariff revenue that is then distributed back to a representative agent: $R_n \equiv \sum_{j=1}^{J+1} \sum_{i=1}^{N+2} \tau_{ni}^j M_{ni}^j$ where $M_{ni} = X_n^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j}$ since processing imports are duty free.

2.8 Balanced Trade

Because income equals expenditure:

$$\sum_{j=1}^{J+1} \sum_{i=1}^{N+1} X_n^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j} = \sum_{j=1}^{J+1} \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} \quad n = 1,...N. \tag{14}$$

The left hand side captures all income accruing to country n and the right hand side captures total world expenditure going to country n. A similar expression expression also holds for China based on ordinary and processing trade:

$$\sum_{j=1}^{J+1}\sum_{i=1}^{N+1} X_o^j \frac{\pi_{oi}^j}{1+\tau_{oi}^j} + \sum_{j=1}^{J+1}\sum_{i=1}^{N} X_p^j \pi_{pi}^j = \sum_{j=1}^{J+1}\sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{1+\tau_{io}^j} + \sum_{j=1}^{J+1}\sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{1+\tau_{ip}^j} \tag{15}$$

Outside of China, aggregate factor payments are given by:

$$\sum_{j=1}^{J+1} \gamma_{l,n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} = w_n L_n \tag{16}$$

and

$$\sum_{j=1}^{J+1} \gamma_{k,n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} = r_n K_n. \tag{17}$$

For China, these expressions are

$$\sum_{j=1}^{J+1} \gamma_{l,o}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{1+\tau_{io}^j} + \sum_{j=1}^{J+1} \gamma_{l,p}^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{1+\tau_{ip}^j} = w_c L_c \tag{18}$$

and

$$\sum_{j=1}^{J+1} \gamma_{k,o}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{1+\tau_{io}^j} + \sum_{j=1}^{J+1} \gamma_{k,p}^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{1+\tau_{ip}^j} = r_c K_c \tag{19}$$

2.9 *Equilibrium*

Definition 1 *Given L_n, K_n, λ_n^j, $g^j\left(d_{ni}\right)$ τ_{in}^j, α_n^j, γ_n^{jk}, $\gamma_{l,n}^j$, $\gamma_{k,n}^j$, ν, and θ^j, an equilibrium under tariff structure τ is a wage vector $\mathbf{w} \in \mathbf{R}_{++}^{\mathbf{N+1}}$, a rental rate vector $\mathbf{r} \in \mathbf{R}_{++}^{\mathbf{N+1}}$, and prices $\{p_n^j\}_{j=1,n=1}^{J,N+2}$ that satisfy equations* (1),(4)-(13), (18) *and* (19) *for all k,i.*

3. Data

Although the Data Appendix discusses our data set in detail, we briefly discuss aspects of it here. Based on data availability, we examine 24 developed and developing countries for the years 2000-2007. We focus on 109 manufacturing sectors and one non-traded sector. Manufacturing industries are at the four-digit ISIC level and the non-traded sector is a composite of services and agriculture.

Trade data outside of China comes from the BACI data base maintained by CEPII. These data are aggregated from the HS six-digit level to the four-digit ISIC level. Trade data for China come from the Customs Administration of China as used in Brandt and Morrow (2017). Because these trade data do not track domestic shipments, we take nominal output data from the UN IDSB data base (also at the four-digit ISIC level) and subtract exports to obtain domestic shipments for all countries. All remaining data used in estimation of the gravity model come from CEPII (distance and contiguity measures) or UN TRAINS (tariff data). Labor endowment is total employment as given in the Penn World Tables 9.0, and the (real) capital stock comes rom the same source.

The cost share of labor $\gamma_{l,n}^{j}$ is given by the the share of total output paid to labor in the UN INDSTAT data set. The total share of intermediate inputs is given by one minus the total share of value added in output for these countries which is also available. This also varies by both country and industry. Capital's share of output in an industry $\gamma_{k,n}^{j}$ is one minus labor's share minus the share of intermediate inputs. We calculate γ_n^{jk} by starting with the world input-output matrix as pubished by Timmer, Dietzenbacher, Los, Stehrer and Vries (2015). At the NACE level, this gives us shares of intermediate inputs accruing to input industries. We denote these as $\tilde{\gamma}^{j'k'}$ where $'$ denotes a NACE sector. Using a concordance available from WITS, and proportionality assumption that the share if an ISIC industry in total inputs in a given NACE industry is proportional to its output relative to other industries in that group, we create ISIC specific intermediate input shares, $\tilde{\gamma}^{jk}$. We then mutliply these by one minus the value added share (which varies across countries) to crate γ_n^{jk}. The Data Appendix describes this in detail.

4. Mapping Theory onto Empirics

4.1 Estimates of θ^j and ν.

As in Eaton and Kortum (2002), we use $\theta^j = 8 \ \forall j$.[12] Because estimates for ν do not exist, we offer a novel strategy here to estimate its value. Using same triad strategy as Caliendo and Parro (2015),

[12] We also set $\sigma^j = 2 \ \forall j$. This does not affect our results at all.

we can obtain the following expression:

$$\left(\frac{\pi^j_{no}\pi^j_{oh}\pi^j_{hn}}{\pi^j_{nh}\pi^j_{ho}\pi^j_{on}}\right) = \left(\frac{(1+\tau^j_{no})(1+\tau^j_{oh})(1+\tau^j_{hn})}{(1+\tau^j_{nh})(1+\tau^j_{ho})(1+\tau^j_{on})}\right)^{-\theta^j} \left(\frac{s^j_{no}}{s^j_{ho}}\right)^{\nu}. \tag{20}$$

Conditional on θ^j, we can use a simple method of moments estimator to obtain a value of ν.[13] The parameter ν parameterizes how productivity draws across ordinary and processing trade in China are correlated. Using the language of discrete choice models (e.g. Berry (1994)), consider ordinary and processing processing trade to reside within a group.[14] As the parameter ν goes to one, the correlation of productivity draws across ordinary and processing within this group goes to one, and as ν approaches zero, the within-group correlation goes to zero. A higher value of ν reduces heterogeneity within the ordinary-processing group which leads to a stronger relationship between the within-group share on the right hand side and ordinary market shares on the left hand side. More casually, this is analogous to techniques developed in Berry (1994) in which across-nest market shares are regressed on within nest shares to identify within-nest elasticities of substitution in nested logit models. To our knowledge, this is the first time such a strategy has been used to estimate the correlation parameter in a multi-variate Frechét distribution.[15] Also note that the use of the triad approach differences out all destination-specific, source-specific, and pair-specific factors which mitigates–though not necessarily eliminates–endogeneity concerns.

Where t indexes years, we estimate the following expression:

$$\ln\left(y^j_{noht}\right) = \nu \ln\left(\frac{s^j_{not}}{s^j_{hot}}\right) + \epsilon^j_{noht}$$

[13]Notice that this does not rely on MFN status. In the extreme case where tariffs are equal across all country pairs, ν is still identified and equation (20) becomes

$$\left(\frac{\pi^j_{no}\pi^j_{oh}\pi^j_{hn}}{\pi^j_{nh}\pi^j_{ho}\pi^j_{on}}\right) = \left(\frac{s^j_{no}}{s^j_{ho}}\right)^{\nu}.$$

[14]Firms in all other countries reside in all other countries reside in their own country-specific groups.

[15]Both Eaton and Kortum (2002) and Ramondo and Rodríguez-Clare (2013) state that this parameter is generally not identified. This is true when the researcher does not take a stand on the nests/groups. However, if a researcher is willing to take a stand on what are the nests/groups, one can use the procedure here to identify the within-group correlation of productivity draws. Also see Khandelwal (2010), Fajgelbaum, Grossman and Helpman (2011), and Edmond, Midrigan and Xu (2015) for examples of nested logits in international trade.

where

$$y^j_{noht} = \left(\frac{\pi^j_{not}\pi^j_{oht}\pi^j_{hnt}}{\pi^j_{nht}\pi^j_{hot}\pi^j_{ont}}\right)\left(\frac{(1+\tau^j_{not})(1+\tau^j_{oht})(1+\tau^j_{hnt})}{(1+\tau^j_{nht})(1+\tau^j_{hot})(1+\tau^j_{ont})}\right)^{\theta^j}$$

and ϵ^j_{noht} is a white noise error term which is normally distributed. The resulting estimate of ν, $\widehat{\nu}$, is 0.71 with a standard error of 0.02 with standard errors clustered by noh triplets. The tight estimate allows us to reject both the null hypotheses that $\nu = 0$ and $\nu = 1$ at conventional levels. We have also experimented with estimating this expression in first differences between 2000 and 2007, this produces an estimate of 0.64.[16] Using a lower value of $\widehat{\nu}$ will reduce the correlation of the draws between ordinary and processing and will increase the welfare effects of Chinese consumers having access to processing goods for a given $\{\lambda^j_o,\lambda^j_p\}$ pair.

4.2 *Measuring* $\lambda^j_n/\lambda^j_{us}$

Because the definition of an equilibrium requires exogenous values for the state of technology in each country, λ^j_n, we follow the structural gravity approach of Levchenko and Zhang (2016) to recover these parameters. This procedure first involves estimating a gravity model for each industry and year. The country-industry fixed effects embody differences in the composite of exogenous TFP, endogenous factor prices, and endogenous intermediate input prices. Factor prices are available in the data described in section 3, and we can solve for endogenous intermediate input prices using the structure of the model as we describe below. These allow us to isolate the state of technology parameter. We first show how to solve for the state of technology,$\lambda^j_n/\lambda^j_{us}$, outside of China, and then in the ordinary sector of China. We then discuss the additional considerations needed when solving for $\lambda^j_p/\lambda^j_{us}$.[17]

[16]The difference between the two can result either some from measurement error whose effect if magnified in first differences or from an error term that is positively correlated with ln $\left(\frac{s^j_{not}}{s^j_{hot}}\right)$.

[17]This differs from the "hat algebra" approach of Jones (1965) and Caliendo and Parro (2015) in that we have to take a stand on the production function whereas they do not. However, their approach does not allow them to estimate productivity which is a central inquiry of this paper and which allows us to examine our the welfare effects of our counterfactuals relative to the welfare effects of observed changes in productivity in China.

4.21 $\lambda^j_n/\lambda^j_{us}$ *outside of China and for Ordinary Trade*

To recover values of $\lambda^j_n/\lambda^j_{us}$, start by taking equation (4) for a given ni pair, divide it by its nn counterpart, and take logs to obtain

$$\ln\left(\frac{\pi^j_{ni}}{\pi^j_{nn}}\right) = \ln\left(\lambda^j_i\left[c^j_i\right]^{-\theta^j}\right) - \ln\left(\lambda^j_n\left[c^j_n\right]^{-\theta^j}\right) - \theta^j \ln\left(\kappa^j_{ni}\right). \tag{21}$$

The first two terms represent the equilibrium effect of differences in average unit costs between n and i. The last term reflects the equilibrium effect of international trade costs. We parameterize κ^j_{ni} as in Eaton and Kortum (2002), Waugh (2010), and Levchenko and Zhang (2016):

$$\ln\left(\kappa^j_{ni}\right) = \sum_{d=1}^{6} \beta^j_d d_{ni,d} + b^j_{ni} + \delta^{j,x}_i + \epsilon^j_{ni}$$

where $d_{ni,d}$ is an indicator variable that turns on when the distance between countries n and i is in the d^{th} distance interval. Intervals are in miles: [0,375); [375,750); [750,1500); [1500,3000); [3000,6000); and [6000,maximum]. β^j_d is then the industry-specific effect of being in this interval. b^j_{ni} is the industry-level effect of *not* sharing a border. When i is a non-China country, $\delta^{j,x}_i \equiv \ln(t^j_i)$ is the exporter effect for country i in industry j. For $i = o$ and $i = p$, respectively,

$$\delta^{j,x}_o \equiv \ln\left\{(t^j_o)^{-\theta^j}\left[1 + \left[\frac{\lambda^j_p}{\lambda^j_o}\left(\frac{c^j_p}{c^j_o}\right)^{-\theta^j}\right]^{\frac{1}{1-\nu}}\right]^{-\nu}\right\}$$

$$\delta^{j,x}_p \equiv \ln\left\{(t^j_p)^{-\theta^j}\left[1 + \left[\frac{\lambda^j_o}{\lambda^j_p}\left(\frac{c^j_o}{c^j_p}\right)^{-\theta^j}\right]^{\frac{1}{1-\nu}}\right]^{-\nu}\right\}.$$

The extra terms for China reflect the correlated Frechét draws and disappear when the correlation goes to zero (i.e. $\nu = 0$).[18]

Moving observed tariffs over to the left hand side delivers the following gravity regression where δ^j_i is a country fixed effect within a given industry-level regression:

[18] They are analogous to the extra price index that appears in two-tier CES utility functions as in Bombardini, Kurz and Morrow (2012).

$$\ln\left(\frac{\pi^j_{ni}}{\pi^j_{nn}}\right) + \theta^j ln(1+\tau^j_{ni}) = \delta^j_i - \delta^j_n + \sum_{d=1}^{6} \beta^j_d d_{ni,d} + b^j_{ni} + \delta^{j,x}_i + \epsilon^j_{ni} \tag{22}$$

where ϵ^j_{ni} is an error term that is assumed to have the usual i.i.d. properties.[19]

With these estimates $\widehat{\delta}^j_n$ in hand, we can exponentiate the ratio, $\widehat{\delta}^j_i/\widehat{\delta}^j_{us}$ and use equation (1) to obtain

$$exp\left(\frac{\widehat{\delta}^j_i}{\widehat{\delta}^j_{us}}\right) = \frac{\lambda^j_i}{\lambda^j_{us}}\left(\frac{c^j_i}{c^j_{us}}\right)^{-\theta^j} \tag{25}$$

At this point, it is common to assume common factor cost shares across countries within an industry, such that c^j_i/c^j_{us} is a function of relative input prices and industry-specific common Cobb-Douglas factor shares across countries α^j_l,α^j_k.[20] This allows the researcher to recover estimates of $\lambda^j_i/\lambda^j_{us}$. However, there is no reason to believe that this restriction holds in the data and, for this reason, we follow Caves, Christensen and Diewert (1982) and use the a superlative measure of relative TFP. This allows us to allow for more general production functions that are well-approximated by the translog function. This allows us to write (25) as

$$exp\left(\frac{\widehat{\delta}^j_i}{\widehat{\delta}^j_{us}}\right) = \frac{\lambda^j_i}{\lambda^j_{us}}\left[\left(\frac{w_i}{w_{us}}\right)^{\tilde{\gamma}^j_{l,i}}\left(\frac{r_i}{r_{us}}\right)^{\tilde{\gamma}^j_{k,i}} \Pi^{J+1}_{k=1}\left(\frac{p^k_i}{p^k_{us}}\right)^{\tilde{\gamma}^{kj}_i}\right]^{-\theta^j} \tag{26}$$

[19]Note that in equation (22) that there is no constant term. This is because the six distance interval dummies would be collinear with a constant as they sum to one. This introduces two wrinkles that are common in this literature but non-standard from an econometric point of view. First, the country-industry fixed effects are not identified relative to a reference group but, rather, reflect the country-industry terms themselves as seen in equations (22). Second, following Eaton and Kortum (2002) and Waugh (2010) the term for the US can be calculated using the following normalization

$$\sum_{i=1}^{N+2} \delta^j_i = 0. \tag{23}$$

Similarly, the US exporter term can be calculated using a similar normalization

$$\sum_{i=1}^{N+2} \delta^{j,x}_i = 0. \tag{24}$$

The first normalization is innocuous as it is a scaling term for productivity parameters as is thus econometrically equivalent to normalizing one price to 1. Here we are simply normalizing the geometric mean of $\lambda^j_i\left(c^j_i\right)^{-\theta_j}$ to be 1.

[20]This is the strategy taken in Waugh (2010) at the national level and Levchenko and Zhang (2016) at the country-industry level.

where $\tilde{\gamma}^j_{l,i} \equiv \frac{\gamma^j_{l,i}+\gamma^j_{l,us}}{2}$. $\tilde{\gamma}^j_{k,i}$ and $\tilde{\gamma}^{kj}_i$ are defined analogously.[21] This calculation is general up to a translog approximation and therefore does not impose that production functions are Cobb-Douglas. However, when we move to our counterfactual analyses, we will impose that these factor cost shares are invariant to equilibrium factor prices (i.e. that production is Cobb-Douglas). In this sense our counterfactuals calculations rely on more restrictive assumptions than our productivity calculations.

Equation (26) shows that we require data on factor prices (w_i and r_i), Cobb-Douglas cost shares, and a value of θ^j to extract values of $\frac{\lambda^j_i}{\lambda^j_{us}}$. Data on w_i, r_i, $\gamma^j_{l,n}$, $\gamma^j_{k,n}$, and γ^{jk}_n are described in section 3, and we use a constant value of $\theta = 8$ for θ^j following Eaton and Kortum (2002). This leaves us requiring empirical counterparts of $\frac{p^k_n}{p^k_{us}}$ to obtain empirical counterparts of $\frac{\lambda^j_i}{\lambda^j_{us}}$ which we obtain following Shikher (2012) and Levchenko and Zhang (2016).[22]

4.22 *Obtaining Values of* $\lambda^j_p/\lambda^j_{us}$

To obtain a value for the state of technology for Chinese processing, we require a little more work. This is because π^j_{pp}=0 and, therefore equation (22) is undefined when processing is the destination location. Because shipments for processing only show up as exports, its fixed effect only identifies the combination of processing's capability and its industry-specific exporting cost. We refer to this

[21] This is the strategy taken by Harrigan (1997) and Morrow (2010). It starts by calculating a relative cost function using country i as a base country (i.e. using country i's cost shares), performing the same exercise using US factor shares, and then taking the geometric mean of these two measures.

[22] To obtain these, take the ratio of π^j_{ii} and $\pi^j_{us,us}$, and equation (10) to obtain: $\frac{\pi^j_{ii}}{\pi^j_{us,us}} = \left(\frac{p^j_i}{p^j_{us}}\right)^{\theta^j} \frac{\lambda^j_i\left(c^j_i\right)^{-\theta^j}}{\lambda^j_{us}\left(c^j_{us}\right)^{-\theta^j}}$. This can easily be manipulated using equation (26) to obtain the empirical counterpart of p^k_n/p^k_{us}, $\widehat{p^k_n/p^k_{us}}$, in terms of data, $\frac{\pi^j_{ii}}{\pi^j_{us,us}}$, and previously estimated values $\frac{\hat{\delta}^j_i}{\hat{\delta}^j_{us}}$: $\widehat{\left(\frac{p^j_i}{p^j_{us}}\right)^{\theta^j}} = \frac{\frac{\pi^j_{ii}}{\pi^j_{us,us}}}{\left[\exp\left(\frac{\hat{\delta}^j_i}{\hat{\delta}^j_{us}}\right)\right]}$. With these in hand, we can easily calculate $\Pi^{J+1}_{k=1}\left(\frac{\hat{p}^k_i}{\hat{p}^k_{us}}\right)^{\gamma^{kj}}$, and obtain values of $\lambda^j_i/\lambda^j_{us}$ from equation (26). To interpret total factor productivity as a cost-shifter relative to the US, our preferred measure of productivity is given by $\left(\frac{\lambda^j_i}{\lambda^j_{us}}\right)^{\frac{1}{\theta^j}}$.

composite as $\delta_p^{j,x}$.[23] However, we can set $t_o^j = t_p^j$, then exponentiate δ_o^j, $\delta_o^{x,j}$ and $\delta_p^{j,x}$, and combine them to obtain:

$$\frac{\exp\left(\widehat{\delta}_o^j\right)\exp\left(\widehat{\delta}_o^{j,x}\right)}{\exp\left(\widehat{\delta}_p^{j,x}\right)} = \frac{\lambda_o^j}{\lambda_p^j}\left(\frac{c_o^j}{c_p^j}\right)^{-\frac{\theta^j}{1-\nu}}. \tag{27}$$

We then make the identifying assumption that $t_p^j = t_o^j$. Because labor and capital are mobile across sectors, these terms cancel but we still require an empirical counterpart for $\Pi_{k=1}^{J+1}\left(\frac{p_p^k}{p_o^k}\right)^{\gamma^{kj}}$. To obtain this, note that, for a given industry, we can use equation (10) for ordinary and processing, and then manipulate the resulting expression to deliver the relative price index for processing relative to ordinary:

$$\frac{p_p^j}{p_o^j} = \left[\pi_{oo}^j + \sum_i^N (1+\tau_{oi}^j)^{\theta^j}\pi_{oi}^j\right]^{-\frac{1}{\theta^j}}.$$

This is a function of observed trade shares, observed tariffs, and θ^j. This expression has the intuitive interpretation that the difference in the price level between ordinary and processing trade is related to the weighted average of tariffs imposed across source countries that ordinary imports are subject to but processing imports are not. With this, and $\lambda_o^j/\lambda_{us}^j$ from above, we can calculate $\lambda_p^j/\lambda_{us}^j$.

5. Results

In this section, we present our results. We start by briefly discussing the gravity models that we estimate. We then present our estimates of total factor productivity for both China's processing and ordinary regimes and find that growth rates for ordinary and processing were nearly identical during this period. However, average unit costs declined more for for ordinary production between 2000 and 2007. This reflects the fact that falling tariffs on inputs diminished the cost advantage to organizing through processing trade. We then explore our counterfactual exercises. We show

[23]Specifically, only the term

$$\delta_p^{j,x} = \ln\left(\lambda_p^j\left[c_p^j t_p^j\right]^{-\frac{\theta^j}{1-\nu}}\left[\lambda_o^j\left[c_o^j t_o^j\right]^{-\frac{\theta^j}{1-\nu}} + \lambda_p^j\left[c_p^j t_p^j\right]^{-\frac{\theta^j}{1-\nu}}\right]^{-\nu}\right).$$

is identified.

that the measured welfare gains to processing receiving duty free exemption are relatively small. However, the welfare losses for Chinese consumers from not being able to purchase from processing firms are large and approximately 5% of real income and 10% of real wages in 2000.[24] Finally, we assess the relative contributions of falling tariffs and rising domestic productivity in China's aggregate transition from processing to ordinary trade. Holding productivity constant, lower statutory tariffs reduced input tariffs, and that this disincentivized firms to organize through processing. We find that that this is consistent with approximately 40% of the total change in the share of processing trade during this period. In comparison, increasing domestic productivity can explain approximately 20%. Both together can explain approximately 50%.[25]

5.1 *Gravity Model*

The first step in our empirical approach is to estimate a gravity model for each industry-year pair j,t. This amounts to estimating equation (22) for each industry and year for which we require productivity estimates. Although the number of estimated coefficients is too large to presented easily, we briefly summarize general patterns for the year 2000. The estimated equations fit the data very well: for 109 estimated equations, the mean and median R^2 are .969 and .973, respectively.[26]. The mean value for the estimated coefficients on the dummy variables for distance are (nearly) monotonically increasing in absolute value with values of .246, -.549, -.879, -1.594, -1.992, -1.992 for the six intervals in increasing order of distance. The dummy variable that takes a value of one if the two countries do *not* share a border is negative for 106 out of 109 industries. Overall, consistent with previous work, we find that the log-linear gravity specification with country-industry fixed effects fits the data extremely well.

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[24]The difference between the two is due to capital income and tariff revenue.

[25]The two individual effects do not sum to the total because of general equilibrium effects that occur within the context of the model.

[26]The minimum is .898 and the maximum is .996

5.2 *Productivity*

Second, we examine productivity in the ordinary and processing sectors in China in 2000. In addition to being of interest on its own, calculating these productivity levels will allow us to use them when assessing the equilibrium effect of their changes on other endogenous variables both on their own and relative to other factors such as declining levels of protection.[27]

Multiple papers have examined relative productivity levels of ordinary and processing firms including Yu (2015), Manova and Yu (2016), Dai et al. (2016), and Li et al. (2017) with mixed results.[28] These mixed results may be due to methodological problems that make comparison of TFP difficult across the two regimes. First, on the output side, output prices across ordinary and processing are difficult to compare because processing export values are only legally allowed to reflect the value of intermediate inputs, labor input, and a fixed margin that reflects capital expenditures.[29] Second, on the input side, using a common intermediate input price deflator is problematic as the differing tariff treatment across these two forms will cause the intermediate input price deflator to be relatively overstated for processing.

While more restrictive in some dimensions (e.g. market structure), our approach makes progress on two issues involved in the comparison of productivity for ordinary and processing production in China. First, by inverting unit costs from expenditure share data, we mitigate issues of output price measurement.[30] Second, by explicitly taking into the divergence in prices paid by ordinary and processing firms due to how imported intermediate inputs are treated, we account for differences in intermediate input price deflators.

Table 1 displays summary statistics for our TFP measures for ordinary and processing trade

[27]This is in contrast to the "hat algebra" approach of Caliendo and Parro (2015) who focus on the equilibrium effect of changes in tariffs and, for this reason, do not calculate productivity levels.

[28]Yu (2015) and Manova and Yu (2016) each find evidence that suggests that processing exporters are less productive than ordinary exporters within an industry while Li et al. (2017), using detailed data on physical quantities, finds the opposite although that paper focuses on one industry.

[29]See Brandt and Morrow (2017) for more on this.

[30]This also allows us to sidestep issues that emerge when quality adjusted prices diverge from observed prices although this will cause unit costs to reflect both TFP and quality differences.

Table 1: Total Factor Productivity in China: Ordinary and Processing Production (Levels)

Variable	N	Mean	Median	sd	min	max
$\left(\widehat{\lambda}^{j}_{o,2000}\right)^{\frac{1}{\theta}}$	109	0.634	0.637	0.270	0.122	1.493
$\left(\widehat{\lambda}^{j}_{p,2000}\right)^{\frac{1}{\theta}}$	108	0.619	0.618	0.254	0.123	1.516
$\left(\widehat{\lambda}^{j}_{p,2000}/\widehat{\lambda}^{j}_{o,2000}\right)^{\frac{1}{\theta}}$	108	0.993	0.992	0.047	0.818	1.107
$\left(\widehat{\lambda}^{j}_{o,2007}\right)^{\frac{1}{\theta}}$	109	0.780	0.788	0.282	0.227	1.544
$\left(\widehat{\lambda}^{j}_{p,2007}\right)^{\frac{1}{\theta}}$	109	0.767	0.781	0.267	0.226	1.392
$\left(\widehat{\lambda}^{j}_{p,2007}/\widehat{\lambda}^{j}_{o,2007}\right)^{\frac{1}{\theta}}$	109	0.988	0.983	0.042	0.882	1.102

Notes: This table presents measures of total factor productivity for ordinary and processing production as represented by estimates of $\lambda^{j}_{o,t}$ and $\lambda^{j}_{p,t}$, $\widehat{\lambda}^{j}_{o,t}$ and $\widehat{\lambda}^{j}_{p,t}$, each raised to the power $\frac{1}{\theta^{j}}$. These estimates are created using the procedure described in section 4 and a value of $\theta^{j} = 8$ for all j. All values are relative to the US.

(and relative to one another) for 2000 and 2007. Specifically, it reports statistics for $(\widehat{\lambda}^{j}_{i}/\widehat{\lambda}^{j}_{us})^{\frac{1}{\theta}}$.[31] The first row shows that the (unweighted) average ordinary productivity in China was 63% of the US while productivity in processing was only slightly lower. Median productivity levels are simular. The average productivity premium of processing relative to ordinary production (the third row) was approximately -1%.[32] Perhaps not surprisingly, there is substantial heterogeneity around that mean with a 95% confidence interval of [0.92,1.07]. Figure 1 presents a histogram depicting this heterogeneity.[33]

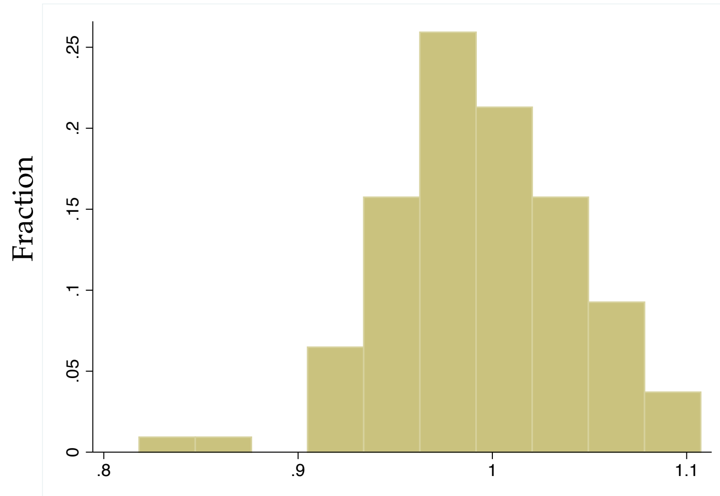
This confidence interval and the heterogeneity implied by it imply that caution should be taken in making statements that firms engaged in ordinary production were or are necessarily less

[31]It is easy to see that this is the proper measure of productivity as a the cost shifter by examining equation (4).

[32]To be clear, the first rows present the means of $\left(\widehat{\lambda}^{j}_{o,2000}/\widehat{\lambda}^{j}_{us,2000}\right)^{\frac{1}{\theta}}$ and $\left(\widehat{\lambda}^{j}_{p,2000}/\widehat{\lambda}^{j}_{us,2000}\right)^{\frac{1}{\theta}}$ the ratio of which need not equal the mean of $\left(\widehat{\lambda}^{j}_{p,2000}/\widehat{\lambda}^{j}_{o,2000}\right)^{\frac{1}{\theta}}$.

[33]The three ISIC sectors in which the processing premium is the lowest are cement, lime and plaster (2694), tobacco products (1600), and cutting, shaping and finishing of stone (2696). The three sectors for which it is the highest are steam generators, except central heating hot water boilers (2813), rubber tires and tubes (2511), and television and radio transmitters (3220).

Figure 1: Histogram of $\left(\lambda_p^j/\lambda_o^j\right)^{1/\theta^j}$



$\left(\lambda_p^j/\lambda_o^j\right)^{1/\theta^j}$

Notes: This table presents a histogram of $\left(\lambda_p^j/\lambda_o^j\right)^{1/\theta^j}$ calculated as described in the text setting $\theta^j = 8 \; \forall j$.

or more productive that firms engaged in processing across industries. The lower three rows present comparable statistics for 2007 and show similar results. Finally, the unweighted average productivity premium for processing was slightly smaller in 2007 than in 2000: -1.2% relative to -0.7%. This suggests that any catch-up in TFP by ordinary firms relative to processing was small relative to overall changes in productivity.

While implied by the results in Table 1, Table 2 presents cumulative productivity growth for China in ordinary and processing production during this time. Consistent with results elsewhere (e.g Brandt, Biesebroeck, Wang and Zhang (2017)), there was tremendous productivity growth with average (unweighted) growth in both ordinary and processing productivity of approximately 29%. These numbers imply per annum productivity growth of approximately 3.7%. For reference, Brandt, Biesebroeck and Zhang (2012) calculate 2.85% per annum growth for incumbent firms in manufacturing using an output based estimation strategy and 7.96% per annum using a value-added approach.

Table 2: Total Factor Productivity in China: Ordinary and Processing Production (Growth)

variable	N	mean	Median	sd	min	max
$\left(\lambda^j_{o,2007}/\lambda^j_{o,2000}\right)^{\frac{1}{\theta}}$	109	1.288	1.247	0.233	0.894	2.158
$\left(\lambda^j_{p,2007}/\lambda^j_{p,2000}\right)^{\frac{1}{\theta}}$	108	1.287	1.242	0.234	0.868	2.132

Notes: This table presents seven year growth rates for total factor productivity for ordinary and processing production. These estimates are created using the procedure described in section 4 and a value of $\theta^j = 8$ for all j.

Perhaps surprisingly, the changes in TFP are very similar across ordinary and processing production. To understand this result better, we use the structure of the model to assess how (average) unit costs changed during this time. Specifically, we examine our estimates of $\delta^j_{o,t}$ and $\delta^j_{p,t}$ and how they changed during this time. Note from equation (26) that these embody differences in productivity, prices of primary factors, and prices of intermediate inputs. Also note that if primary factors of production are mobile between ordinary and processing trade, then the only differences remaining will be those in productivity and the price of intermediate inputs. Table 3 presents proportional changes in unit costs for processing (in the first row), ordinary (in the second row), and the relative change in processing relative to ordinary.[34] For each, a value of one indicates that unit costs were unchanged, values less than one indicate that unit costs fell, and values greater than one indicate that unit costs increased.

The first row shows that average unit costs in 2007 were only 82.8% as much as they were in 2000 for ordinary production, while average unit costs for processing in 2007 were 86% of what they were in 2000. The final row shows that on average, processing unit costs fell by 4.2 percentage points less than they did for ordinary during this time. Combining these results with the small differences in TFP growth (table 2) suggests that unit costs fell more for ordinary trade than for processing but that it was because falling input tariffs which *diminished* the price advantage to organizing through processing that are behind this rather than differences in TFP.

[34] Note that δ^j_i delivers the equilibrium effect of differences in average unit costs. $\left(\delta^j_i\right)^{-\frac{1}{\theta^j}}$ transforms this into differences in average unit costs.

Table 3: Average Unit Cost: Ordinary and Processing Production (Growth)

Variable	N	Mean	Median	sd	min	max
$\left(\frac{\widehat{\delta}^j_{o,2007}}{\widehat{\delta}^j_{o,2000}}\right)^{-\frac{1}{\theta^j}}$	109	0.828	0.836	0.134	0.539	1.135
$\left(\frac{\widehat{\delta}^j_{p,2007}}{\widehat{\delta}^j_{p,2000}}\right)^{-\frac{1}{\theta^j}}$	108	0.860	0.863	0.163	0.501	1.395
$\left(\frac{\widehat{\delta}^j_{p,2007}\widehat{\delta}^j_{o,2000}}{\widehat{\delta}^j_{p,2000}\widehat{\delta}^j_{o,2007}}\right)^{-\frac{1}{\theta^j}}$	108	1.042	1.048	0.100	0.591	1.384

Notes: This table presents measures of average unit costs for ordinary and processing production as represented by estimates of $\left(\widehat{\delta}^j_o\right)^{-\frac{1}{\theta^j}} = c^j_o / \left(\lambda^j_{o,t}\right)^{\frac{1}{\theta^j}}$ and $\left(\widehat{\delta}^j_p\right)^{-\frac{1}{\theta^j}} = c^j_p / \left(\lambda^j_{p,t}\right)^{\frac{1}{\theta^j}}$. These estimates are created using the procedure described in section 4 and a value of $\theta^j = 8$ for all j. All values are relative to the US.

Combined, we emphasize the following three facts from these results. First, while the levels are similar, there was heterogeneity in the productivity premium of processing relative to ordinary in both 2000 and 2007. This is inconsistent with results that suggest that one form of trade systematically has a higher level of productivity than the other within an industry. Second, changes in TFP across the two organizational forms were very similar during this time. Finally, third, falling input tariffs caused the unit cost advantage of organizing through processing relative to ordinary to diminish during this period.

5.3 *Counterfacuals: The Welfare Effects of Processing*

We now perform a series of counterfactual experiments to assess the impact of the processing regime on various economic outcomes in China. Before proceeding to our counterfactual experiments, we briefly assess model fit by comparing model generated data to the raw data. To do this we use our estimated parameters to solve for a baseline equilibrium including the endogenous trade shares $\widehat{\pi}^j_{ni}$.[35] As suggested by the high R^2 statistics from the gravity model estimation, the π^j_{ni} and its model generated counterpart, $\widehat{\pi}^j_{ni}$, are highly correlated. The correlation between the two is

[35]In the context of these experiments, "hats" represent model-generated data while variables without hats correspond to raw data.

Table 4: Real Wages and Income: Counterfactual Simulations

Specification Number	Specification Description	Nominal Wage (rel. to US) (1)	Price Index Price Index (2)	Real Wage (rel. to US) (3)	Real Income (rel. to US) (4)
(1)	Benchmark	0.0477	0.5953	0.0801	0.1778
(2)	$\tau_{pi}^{j} = \tau_{oi}^{j}$	0.0474	0.5939	0.0798	0.1778
(3)	$\kappa_{op}^{j} = \kappa_{pp}^{j} = 1$	0.053	0.6007	0.0883	0.1867
(4)	$\kappa_{op}^{j} = \kappa_{pp}^{j} = 1,\, \lambda_{o}^{j} = \lambda_{p}^{j}$	0.0547	0.6089	0.0898	0.1885
(5)	$\kappa_{op}^{j} = \kappa_{pp}^{j} = 1,\, \tau_{pi}^{j} = \tau_{oi}^{j} \geq 0$	0.0532	0.6073	0.0877	0.1864
(6)	$\kappa_{ip}^{j} = \infty\ \forall i,j$	0.0457	0.5812	0.0787	0.1770

Notes: This table presents results of counterfactual simulations as discussed in section 5.3. The first column numbers the specification, the second column briefly describes the specification, the third column presents the simulated value of the nominal wage of labor relative to the US, The fourth column presents the value of the price of one unit of consumption relative to the US $\left(p_n/p_{us} \equiv \Pi_{j=1}^{J}\left(p_n^j/p_{us}^j\right)\right)$. The fifth column presents the real wage relative to the US. The sixth column presents real income relative to the US. Row (1) represents the baseline equilibrium in which actual values of productivity and tariffs are imposed. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do. Row (3) allows processing firms to sell to to the ordinary sector and to the processing sector without any trade costs. Row (4) is the same as row (3) except that the state of technology in processing is imposed to be the same as the actual value for ordinary but with imperfect correlation of draws. Row (5) is the same as row (3) except that processing firms pay the same tariffs on imports that ordinary firms do. Row (6) imposes infinite trade costs on all shipments out of the processing sector.

0.90 and the slope coefficient from a regression of $\widehat{\pi}_{ni}^{j}$ on π_{ni}^{j} is 0.84.[36] As a result, we fit the biltateral trade share data quite well. Because of our interest in ordinary relative to processing trade we also examine the model implied share of processing exports in total exports.[37] In the data the share of ordinary exports in 2000 was 0.60% while the model delivers 0.59%. Taking into consideration that this is a non-targeted moment in our estimation, we find this to be reassuring.[38]

Processing is not a single policy lever: it is a combination of policies each of which have potentially different effects on economic outcomes. For this reason, our counterfactuals examine policies one by one before examining their joint effects. As our criteria for welfare, we calculate real wages and real income relative to the United States in the context of our model.

[36]The coefficient on a reverse regression of π_{ni}^{j} on $\widehat{\pi}_{ni}^{j}$ is 0.97.

[37]Specifically, we compare $\frac{\sum_{i,j} X_{ip}^{j}}{\sum_{i,j} X_{io}^{j} + X_{ip}^{j}}$ to $\frac{\sum_{i,j} \widehat{X}_{ip}^{j}}{\sum_{i,j} \widehat{X}_{io}^{j} + \widehat{X}_{ip}^{j}}$

[38]While the gravity model is a best fit OLS estimator for trade shares at the sectoral level, fitting *aggregate* shares across industry-level gravity models is not necessarily implied.

We now move to the counterfactuals themselves. Table 4 presents our results. The first row is not a counterfactual experiment. Instead, it is a benchmark simulation that feeds in $\widehat{\lambda}^{j}_{i,2000}$ and observed tariffs $\tau^{j}_{ni,2000}$. The outputs of this exercise are model-implied nominal wages, the price index (i.e. the price of one unit of utility), the real wage (the ratio of the nominal wage to the price index), and real income. Examining row 1, nominal wages are approximately 5% of US nominal wages but a lower price index means that real wages are slightly higher. A similar pattern holds when looking at real income.

We then ask what is the benefit to Chinese consumers coming from the duty free treatment that processing receives. We do this in row 2 by asking what would happen to welfare if processing were subjected to the same tariffs as ordinary production. More precisely, we set $\tau^{j}_{pi} = \tau^{j}_{oi}$ instead of setting $\tau^{j}_{pi} = 0$ as in the benchmark case (row 1). Although the full set of general equilibrium interactions is obviously complex, our prior is that there should be a negative effect on demand for primary factors of production due to decreased export competitiveness as intermediate input prices rise. The price index–which is a function of factor prices–should also fall but by less due to rising intermediate input prices. This should lead to a small negative change in real wages. Looking at columns (3) and (4), this prediction is largely borne out as real wages and income fall slightly. However, these changes are quantitatively small. This reflects the small share of imports in total economic activity and is consistent with the small effects of incremental trade liberalization found in Eaton and Kortum (2002) and Caliendo and Parro (2015).

Our second counterfactual experiment examines the other major policy component of processing: the restriction from selling to domestic agents. Row 3 of table 4 presents our results for the counterfactual in which processing firms are allowed to sell to domestic consumers but keep their levels of productivity as in the data. Specifically, we impose $\kappa^{j}_{pp} = \kappa^{j}_{op} = 1$. Differences in productivity between the two forms of organization are important for understanding this counterfactual. If ordinary firms and processing firms share the same (perfectly correlated) productivity levels but consumers are allowed to buy from processing firms, there is no welfare gain because the menu of prices is unchanged. However, less than perfectly correlated productivity draws introduce the possibility of welfare gains due to comparative advantage. For this, our estimate of ν is important: if it is lower than out estimated value–as when we identify it in first differences–this will generate larger welfare gains from allowing Chinese consumers and firms to purchase processing output.

We find major welfare effects. In the context of our model, a counterfactual world in which Chinese consumers can buy from processing firms displays real wages that are 10% higher (0.82 percentage points) and real income that is 5% higher (0.89 percentage points) than in the benchmark equilibrium. The reason that these effects is so large is that, *taking transport costs into account*, consumers spend a much larger share of their incomes on domestically provided goods than imported goods. Consequently, any policy that affects the menu of prices presented by domestic firms will have a much larger effect than a policy that affects the price charged on imports.

Perhaps surprisingly, it is not even necessary for the states of technology λ_o^j,λ_p^j to be different, only that they are not perfectly correlated. To show this, row 4 of table 4 presents counterfactual welfare results in which processing firms are allowed to sell domestically $\kappa_{pp}^j = \kappa_{op}^j = 1$, possess the same state of technology as ordinary production $\lambda_{p,2000}^j = \lambda_{o,2000}^j$, but have productivity draws that are not perfectly correlated with those for ordinary firms, $\nu = 0.71$. Welfare results are largely the same suggesting that the mere presence of non-perfectly correlated draws generates these welfare effects.

Finally, we consider two possible hypothetical situations that correspond to the dismantling of the processing regime. First, row 5 considers a case in which processing production loses its preferential tariff access but is allowed to sell domestically: $\tau_{pi}^j = \tau_{oi}^j$ and $\kappa_{pp}^j = \kappa_{op}^j = 1$. We allow processing in this case to keep its estimated exogenous productivity level and $\nu = 0.71$. Second, row 6 consider a case in which the processing sector disappears and all Chinese production occurs under the ordinary regime. This is done by setting $\kappa_{ip}^j = \infty \; \forall i,j$

Row 5 shows that, even if processing loses its tariff free access to imported inputs, the gains from consumers being able to access goods produced by these firms are nearly as large as the case in which processing firms can sell domestically but possesses preferential tariff treatment. Row 6 shows that these gains are dependent on productivity differences. If there is no processing sector such that all firms in a sector share the same (ordinary) productivity level, face input tariffs, but can sell domestically, welfare is slightly lower than in the benchmark case.[39]

5.4 *Counterfacuals: The Organization of Trade*

In a second and distinct set of counterfactuals, we assess the ability of the model to reproduce changes in the share of aggregate exports that are organized through processing. A small literature has examined the determinants of the increasing share of Chinese exports organized through ordinary *vis-a-vis* processing trade between 2000 and 2007. In complementary papers, Brandt and Morrow (2017) argue that falling levels of protection on intermediate inputs and capital equipment were a major contributor because this provided firms with a diminishing incentive to organize through processing and obtain duty free inputs. Manova and Yu (2016) argue that financial constraints were also important in explaining this evolution. While valuable contributions, both rely on reduced form estimated estimation that cannot identify aggregate effects nor do they provide structural interpretation of the reduced form parameters.

We examine the evolution of the aggregate share of exports organized through ordinary trade through a set well-defined quantitative experiments. Using a difference-in-difference approach, Brandt and Morrow (2017) argue that this was related to a diminishing incentive to organize through processing trade due to falling input tariffs as well as an expansion of the Chinese domestic market relative to external markets. Due to data limitations, they could not directly examine the effect of rising productivity in the ordinary sector relative to in processing. The counterfactuals in this sub-section fill two holes in this literature: first, we examine the aggregate effect of falling input tariffs on the evolution of ordinary and processing trade in China because this aggregate effect is not identified in reduced form econometric work. Second, by exploiting our productivity measures derived in section 5.2, it can examine the role of changing productivity levels in China.

Table 5 presents raw data for our sample of countries. In 2000, a little more than 60% of Chinese exports to the countries *in our sample* we conducted through processing trade and, by 2007, this

[39] Because there is literally no processing sector in this case, ν plays no role.

Table 5: Processing Exports as a Share of Total Exports: 2000-2007 (Data)

	2000	2001	2002	2003	2004	2005	2006	2007
$\frac{\sum_{j,i} X^j_{ip}}{\sum_{j,i} X^j_{ip}+X^j_{io}}$	0.604	0.602	0.601	0.576	0.571	0.543	0.518	0.475

Notes: This table presents data on the share of Chinese exports to the countries listed in the Data Appendix that is organized through processing trade.

Table 6: Processing Exports as a Share of Total Exports: 2000 and 2007 (Counterfactuals)

Specification	$\widehat{\tau}^j_{oi,2007}$	$\widehat{\lambda}^j_{o,2007}$	$\widehat{\lambda}^j_{p,2007}$	$\frac{\sum_{j,i} \widehat{X}^j_{ip,2007}}{\sum_{j,i} \widehat{X}^j_{ip,2007}+\widehat{X}^j_{io,2007}}$
	(1)	(2)	(3)	(4)
1	$\tau^j_{oi,2000}$	$\lambda^j_{o,2000}$	$\lambda^j_{p,2000}$	0.598
2	$\tau^j_{oi,2007}$	$\lambda^j_{o,2000}$	$\lambda^j_{p,2000}$	0.548
3	$\tau^j_{oi,2000}$	$\lambda^j_{o,2007}$	$\lambda^j_{p,2007}$	0.575
4	$\tau^j_{oi,2007}$	$\lambda^j_{o,2007}$	$\lambda^j_{p,2007}$	0.532

Notes: This table presents results of counterfactual simulations as discussed in section 5.3. The first column states the level that tariffs take in 2007 in China in the simulation. The second column states the ordinary state of technology takes its 2007 level in China in the simulation. The third column states the level that the state of technology for processing takes its 2007 level in China in the simulation. The fourth column displays the model generated share of aggregate exports that are organized through processing trade. See table 5 for actual shares of aggregate trade organized through processing for the countries in the sample. Specification 1 presents model generated data using actual tariffs and states of technology. Specification 2 changes tariffs to their 2007 level. Specification 3 changes states of technology to their 2007 levels. Specification 4 changes both tariffs and states of technology to their 2007 levels.

share had fallen a little more than 20% (12.9 percentage points) to 47.5%.[40]

Table 6 presents our counterfactual simulations. In each row, the second column describes which set of tariffs we feed into our model. For example, if $\widehat{\tau}^j_{oi,2007} = \tau^j_{oi,2007}$, this means that set Chinese tariffs to their 2007 level and, if $\widehat{\tau}^j_{oi,2007} = \tau^j_{oi,2000}$, we hold tariffs constant at their 2000 levels. The third and fourth columns state which set of productivity estimates we feed into the model. The final column presents counterfactual calculations of the share of processing in total exports.

Row 1 holds tariffs and productivity constant at their 2000 level. The predicted aggregate share

[40]This change is larger than that documented in Brandt and Morrow (2017) given that our sample of destination countries is smaller. However, given that our estimates of productivity are generated from this sample as well, the proportion of this total change that can be accounted for by productivity changes is interesting in and of itself.

of exports organized through ordinary trade (0.598) is very close to the actual number (0.604). Row 2 feeds in actual changes in tariffs in China holding all productivity terms constant.[41] Lower levels of protection imply lower levels of input tariffs and a lesser incentive for China's exports to be organized through ordinary trade. Consistent with this idea, our model implies that approximately 38% of the total change in ordinary exports (approximately 5 percentage points) can be explained by lower tariffs in China. The third row keeps tariffs constant but feeds in the observed change in productivity keeping tariffs at their 2000 level. The differential change in ordinary productivity relative to processing trade can explain approximately 18% (1.3 percentage points) of the observed change. Row 4 feeds in both lower tariffs and the observed changes in productivity for the ordinary and processing sectors. Combined, lower levels of protection and observed levels of productivity growth are consistent with approximately 50% (6.6 percentage points) of the change in ordinary relative to processing trade.

In summary, lower levels of protection do appear to have increased the share of ordinary trade in total exports between 2000 and 2007. However, they are unable to explain more than 38% of the total change. Similarly, increasing productivity in ordinary production relative to processing, and increasing productivity overall explain approximately 18% of the total change. Combined these two effects are consistent with approximately 50% of the total change. This suggests that other factors such changes in Chinese relative to global demand, changing capital market conditions as in Manova and Yu (2016) or other non-modelled preferences are needed to explain the remainder of the change.

6. Conclusion

Export processing zones and processing activities in general have figured prominently in the strategies of many export-oriented developing countries. Despite much debate as to their effectiveness, simple cost-benefit analyses have been lacking. This paper seeks to fill this hole with a

[41] Tariffs in all other countries are also held constant. This is unlikely to affect the relative share of processing trade in Chinese exports as both face the same tariffs in destination countries.

quantitative assessment of China's export processing regime for the years 2000 through 2007. Using the machinery of the Caliendo and Parro (2015) and Levchenko and Zhang (2016) multi-sector extensions of Eaton and Kortum (2002), we assessed the quantitative importance of two common characteristics of processing regimes: export processing firms are able to import intermediate inputs duty free but are unable to sell their output on the domestic market.

We emphasize three results from our analysis. First, for China in the years considered, productivity differs between ordinary and processing production suggesting that firms engaging in processing are not simply replicating ordinary production. Also, sometime during the period considered, average productivity in ordinary caught up and surpassed productivity in processing. Second, the welfare effects of productivity being afforded duty free imports is not quantitatively important. This is in line with other work suggesting that the gains from incremental trade liberalization are small e.g. Eaton and Kortum (2002), Costinot et al. (2012), and Caliendo and Parro (2015). However, third, there are large welfare gains associated with allowing Chinese firms who are engaged in processing to sell domestically. This result is closely linked to the fact that productivity differs across ordinary and processing and this domestic market liberalization would allow for a new form of gains from trade.

Processing is often through to entail benefits such as foreign exchange accumulation and learning-by-doing. These do not show up in our model and their quantitative importance must be large to justify the current processing regime. However, this begins up another question related to optimal policy: is there another set of policies that can encourage this foreign exchange and knowledge accumulation that does not entail the costly distortions that come from processing firms not being allowed to sell domestically?

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Appendix A. Proofs

A. Price Distributions

As in Eaton and Kortum (2002), we start by defining the distribution of equilibrium prices in each industry-destination pair nj. The distribution of prices that each non-Chinese exporting country i offers each destination n in industry n is defined to be

$$G_{ni}^{j}(p) \equiv Pr[p_{ni}^{j}(\omega^{j}) < p].$$

Using the properties of the Frechét, this can be solved to be

$$G_{ni}^{j}(p) = 1 - \exp\left[\lambda_i^j \left(c_i^j \kappa_{ni}^j\right)^{-\theta^j} p^{-\theta^j}\right]. \tag{A1}$$

For Chinese exporters (the sum of ordinary and processing exporters), the multivariate Frechét, delivers the following expression

$$G_{nc}^{j}(p) = 1 - \exp\left[\left(\left(\lambda_o^j\right)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j\right)^{-\frac{\theta^j}{1-\nu}} + \left(\lambda_p^j\right)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j\right)^{-\frac{\theta^j}{1-\nu}}\right)^{1-\nu} p^{\theta^j}\right]. \tag{A2}$$

A.1 Non-China Destinations

The distribution of prices that n actually pays in industry j is given by

$$G_n^j = 1 - \left\{\left[\prod_{i=1}^{N} G_{ni}^j(p)\right]\left[1 - G_{nc}^j(p)\right]\right\}.$$

Using equations (A1), (A2), and (A.1), the distribution of prices in any non-Chinese destination market is given by

$$G_n^j = 1 - \exp\{-\Phi_n^j p^{\theta^j}\}$$

where

$$\Phi_n^j \equiv \left[\left(\lambda_o^j\right)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j\right)^{-\frac{\theta^j}{1-\nu}} + \left(\lambda_p^j\right)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j\right)^{-\frac{\theta^j}{1-\nu}}\right]^{1-\nu} + \left[\sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{ni}^j\right)^{-\theta^j}\right]$$

A.2 Ordinary Importing in China

The distribution of prices that the ordinary sector actually pays in industry j is given by

$$G_o^j = 1 - \left\{\left[\prod_{i=1}^{N} G_{on}^j(p)\right]\left[1 - G_{on}^j(p)\right]\right\}.$$

Note that the last term is different because the ordinary sector cannot purchase from processing product lines in China. The distribution of prices in the Chinese ordinary processing sector is given by

$$G_o^j = 1 - \exp\{-\Phi_o^j p^{\theta^j}\}$$

where

$$\Phi_o^j \equiv \lambda_o^j \left(c_o^j \kappa_{no}^j\right)^{-\theta^j} + \sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{oi}^j\right)^{-\theta^j}.$$

A.3 Processing Importing in China

The distribution of prices that the ordinary sector actually pays in industry j is given by

$$G_o^j = 1 - \left\{ \left[\prod_{i=1}^{N} G_{oi}^j(p)\right] \left[1 - G_{oc}^j(p)\right] \right\}$$

Because processing firms are unrestricted in whom they can buy from. Therefore, the distribution of prices in the Chinese processing processing sector is given by

$$G_p^j = 1 - \exp\{-\Phi_p^j p^{\theta^j}\}$$

where

$$\Phi_p^j \equiv \left[\left(\lambda_o^j\right)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{po}^j\right)^{-\frac{\theta^j}{1-\nu}} + \left(\lambda_p^j\right)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{pp}^j\right)^{-\frac{\theta^j}{1-\nu}} \right]^{1-\nu} + \sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{pi}^j\right)^{-\theta^j}$$

B. Expenditure Shares

B.1 Non-China Sources, Non-China Destinations

For non-China destinations, expenditure shares π_{ni}^j are straightforward applications of the Frechét machinery. As in Eaton and Kortum (2002) (pg. 1748), the precise definition of π_{ni}^j is $\pi_{ni}^j \equiv Pr\left[p_{ni}^j(\omega^j) \leq \min\left\{p_{ns}^j(\omega^j); s \neq i\right\}\right] = \int_0^\infty \prod_{s\neq i}\left[1 - G_{ns}^j(p)\right] dG_{ni}^j(p)$. Using equations (A.1) and (A.1), this is equivalent to

$$\pi_{ni}^j = \int_0^\infty \exp\left[-\Phi_n^j p^{\theta^j}\right] dG_{ni}^j(p) = \frac{\lambda_i^j (c_i^j \kappa_{ni}^j)^{-\theta^j}}{\left[\left(\lambda_o^j\right)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{nC}^j\right)^{\frac{-\theta^j}{1-\nu}} + \left(\lambda_p^j\right)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{nC}^j\right)^{\frac{-\theta^j}{1-\nu}}\right]^{1-\nu} + \sum_{i'=1}^{N} \lambda_{i'}^j \left(c_{i'}^j \kappa_{ni'}^j\right)^{-\theta^j}}.$$

B.2 Non-China Sources, China as a Destination

Because processing firms in China can import from any location, expenditure shares are very similar to the expression above:

$$\pi_{pi}^j = \int_0^\infty \exp\left[-\Phi_p^j p^{\theta^j}\right] dG_{pi}^j(p) = \frac{\lambda_i^j (c_i^j \kappa_{pi}^j)^{-\theta^j}}{\left[\left(\lambda_o^j\right)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{po}^j\right)^{\frac{-\theta^j}{1-\nu}} + \left(\lambda_p^j\right)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{pp}^j\right)^{\frac{-\theta^j}{1-\nu}}\right]^{1-\nu} + \sum_{i'=1}^{N} \lambda_{i'}^j \left(c_{i'}^j \kappa_{pi'}^j\right)^{-\theta^j}}.$$

Because ordinary firms cannot purchase from processing firms, the share of ordinary firm expenditures can be derived using the expression above and $\kappa_{op}^j = \infty$.

$$\pi_{oi}^j = \int_0^\infty \exp\left[-\Phi_o^j p^{\theta^j}\right] dG_{oi}^j(p) = \frac{\lambda_i^j (c_i^j \kappa_{oi}^j)^{-\theta^j}}{\lambda_o^j \left(c_o^j \kappa_{po}^j\right)^{-\theta^j} + \sum_{i'=1}^{N} \lambda_{i'}^j \left(c_{i'}^j \kappa_{oi'}^j\right)^{-\theta^j}}.$$

B.3 Chinese Ordinary Exports to Non-China Destinations

For this section, it helps to define two small pieces of additional notation. First, is the minimum productivity level that a Chinese ordinary exporter must have to charge a delivery price of a given variety in industry j in market n that is lower than all other non-Chinese exporters.

$$w_n^j(\omega^j) \equiv c_o^j \kappa_{no}^j \max_{i=1, i\neq o,p} \left\{ \frac{z_i^j(\omega^j)}{c_i \kappa_{ni}^j} \right\}.$$

Under the Fréchet distribution, $w_n^j(\omega^j)$ will be distributed as follows

$$G_n^j(w_n^j) = 1 - \exp\left[\underbrace{-(c_o\kappa_{no})^{\theta^j} \sum_{i\neq o,p} \lambda_i (c_i \kappa_{ni})^{-\theta^j}}_{\tilde{\Phi}_n^j} w_n^{-\theta^j} \right] \tag{A3}$$

Second, define $\mu_n^j = \frac{c_o^j \kappa_{no}^j}{c_p^j \kappa_{np}^j}$ as the relative delivery prices (exclusive of productivity differences) for ordinary and processing shipments of a variety of good j to destination n.
The share of expenditure on goods accruing to the ordinary sector in China in a given destination-industry pair nj is given by

$$\pi_{no}^j = Prob(z_o^j > \max\{\mu_n^j, w_n^j\}).$$

This is the probability that a given variety provided through ordinary trade is cheaper than both the same variety provided through processing *and* also cheaper than all other non-Chinese exporters.

$$\pi_{no}^j = \int_0^\infty \left[\int_0^{w_n^j/\mu_n^j} \int_w^\infty f(z_o^j, z_p^j) dz_o^j dz_p^j + \int_{w_n^j/\mu_n^j}^\infty \int_{\mu_n^j z_p^j}^\infty f(z_o^j, z_p^j) dz_o^j dz_p^j \right] g(w_n) dw_n$$

where

$$\int_0^{w_n^j/\mu_n^j} \int_w^\infty f(z_o^j, z_p^j) dz_o^j dz_p^j = \frac{w_n^j}{\mu_n^j} - \exp\left[- \left(\lambda_o^j w_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p^j \left(\frac{w_n^j}{\mu_n^j} \right)^{-\frac{\theta^j}{1-\nu}} \right)^{1-\nu} \right]$$

$$\int_{w_n^j/\mu_n^j}^\infty \int_{\mu_n^j z_p^j}^\infty f(z_o^j, z_p^j) dz_o^j dz_p^j = 1 - \frac{w_n^j}{\mu_n^j} - \frac{\lambda_p^j}{\lambda_o^j \left(\mu_n^j\right)^{\frac{-\theta^j}{1-\nu}} + \lambda_p^j} \left[1 - \exp\left[- \left(\lambda_o^j w_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p^j \left(\frac{w_n^j}{\mu_n^j} \right)^{-\frac{\theta^j}{1-\nu}} \right)^{1-\nu} \right] \right]$$

Adding last two expressions delivers

$$\frac{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}}}{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p} \left\{ 1 - exp[-(\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}})^{1-\nu} w_n^{-\theta^j}] \right\} \tag{A4}$$

Integrating equations (A4) over w_n, we get

$$\begin{aligned}
\pi_{no} &= \frac{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}}}{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p} \int_0^\infty \Big\{ 1 - exp[-(\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}})^{1-\nu} w_n^{-\theta^j}] \Big\} g(w_n) dw_n \\
&= \frac{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}}}{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p} - \frac{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}}}{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p} \int_0^\infty \theta^j \lambda_{w_n} exp\Big[- [(\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}})^{1-\nu} + \lambda_{w_n}] w_n^{-\theta^j} \Big] dw_n \\
&= \frac{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}}}{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p} - \frac{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}}}{\lambda_o \mu_n^{-\frac{\theta^j}{1-\nu}} + \lambda_p} \frac{\lambda_{w_n}}{(\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}})^{1-\nu} + \lambda_{w_n}} \\
&= \frac{\lambda_o}{\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}}} \frac{(\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}})^{1-\nu}}{(\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}})^{1-\nu} + \lambda_{w_n}}
\end{aligned}$$

where the second equality follows from the distribution function (A3). Substitute in $\mu_n = \frac{c_o \kappa_{no}}{c_p \kappa_{np}}$ and $\lambda_{wn} = (c_o \kappa_{no})^{\theta^j} \sum_{i \neq o,p} \lambda_i (c_i \kappa_{ni})^{-\theta^j}$ into the last equality, π_{no} can be rewritten as

$$\pi_{no} = \frac{\lambda_o (c_o \kappa_{no})^{-\frac{\theta^j}{1-\nu}}}{\lambda_o (c_o \kappa_{no})^{-\frac{\theta^j}{1-\nu}} + \lambda_p (c_p \kappa_{np})^{-\frac{\theta^j}{1-\nu}}} \frac{[\lambda_o (c_o \kappa_{no})^{-\frac{\theta^j}{1-\nu}} + \lambda_p (c_p \kappa_{np})^{-\frac{\theta^j}{1-\nu}}]^{1-\nu}}{[\lambda_o (c_o \kappa_{no})^{-\frac{\theta^j}{1-\nu}} + \lambda_p (c_p \kappa_{np})^{-\frac{\theta^j}{1-\nu}}]^{1-\nu} + \sum_{i \neq o,p} \lambda_i (c_i \kappa_{ni})^{-\theta^j}}$$

Note that the term $\frac{\lambda_o}{\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}}}$ captures the relative size of ordinary trade in market n. It is higher when the fundamental productivity of ordinary trade λ_o is relative higher, or relative cost of ordinary trade μ_n is lower. The second term $\frac{[\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}}]^{1-\nu}}{[\lambda_o + \lambda_p \mu_n^{-\frac{\theta^j}{1-\nu}}]^{1-\nu} + \lambda_{w_n}}$ captures the market share of China as a whole in country n.

B.4 Chinese Processing Exports to Non-China Destinations

Similarly, The expenditure share on goods from processing sector is

$$\pi_{np} = \frac{\lambda_p \mu_n^{-\frac{\theta_j}{1-\nu}}}{\lambda_o + \lambda_p \mu_n^{-\frac{\theta_j}{1-\nu}}} \frac{[\lambda_o + \lambda_p \mu_n^{-\frac{\theta_j}{1-\nu}}]^{1-\nu}}{[\lambda_o + \lambda_p \mu_n^{-\frac{\theta_j}{1-\nu}}]^{1-\nu} + \lambda_{w_n}} \tag{A5}$$

Appendix B. Data Appendix

A. Countries

The following countries comprise our dataset: Australia*, Austria*, Canada*, China* (ordinary and processing), Colombia, Ecuador, Finland*, France*, Germany*, Great Britain*, Hungary*, Indonesia*, India*, Italy*, Japan*, Morocco, Malaysia, Norway, Poland*, Portugal*, Slovenia*, South

Korea*, Spain*, Sweden*, United States*, Vietnam. Countries with asterisks are in the WIOD data set of Timmer et al. (2015). This is relevant in the data construction process described below.

B. Industries

In addition to a non-traded sector, the following 118 four-digit ISIC revision 3 industries comprise our dataset although missing data for output leads to fewer industries depending on the industry: 1511, 1512, 1513, 1514, 1520, 1531, 1532, 1533, 1541, 1542, 1543, 1544, 1549, 1551, 1552, 1553, 1554, 1600, 1711, 1721, 1722, 1723, 1729, 1730, 1810, 1820, 1911, 1912, 1920, 2010, 2021, 2022, 2023, 2029, 2101, 2102, 2109, 2211, 2212, 2213, 2219, 2221, 2222, 2411, 2412, 2413, 2421, 2422, 2423, 2424, 2429, 2430, 2511, 2519, 2520, 2610, 2691, 2692, 2693, 2694, 2695, 2696, 2699, 2710, 2720, 2811, 2812, 2813, 2893, 2899, 2911, 2912, 2913, 2914, 2915, 2919, 2921, 2922, 2923, 2924, 2925, 2926, 2927, 2929, 2930, 3000, 3110, 3120, 3130, 3140, 3150, 3190, 3210, 3220, 3230, 3311, 3312, 3313, 3320, 3330, 3410, 3420, 3430, 3511, 3512, 3520, 3530, 3591, 3592, 3599, 3610, 3691, 3692, 3693, 3694, 3699. We discuss selection and the unbalanced nature of our dataset below.

C. Data Sources

The source of trade data for China is the same as in Brandt and Morrow (2017) which comes at the HS six-digit level and is disaggregated by ordinary and processing trade for the years 2000-2006. This paper extends the analysis to 2007. For the rest of the world, trade data is available through UN Comtrade (via BACI) and is also available at the HS six-digit level for the same time period. As we discuss below, we aggregate this up to the four-digit ISIC level using a crosswalk.[42]

Output data comes from the United Nations Industrial Demand-Supply Balance (IDSB) Database data set. This data set contains both output and world exports data which can be used to create domestic sales data. Because not every country-industry pair has output or world exports data, we start by interpolating some values and then establish a maximum number of missing observations beyond which we drop the country. We do this as follows: we start by merging this data with the BACI trade data. We then run a regression of world exports from the IDSB data base on total exports as found in the BACI data. An observation in this regression is at the 4-digit ISIC-country-year level. The R^2 from this regression is 0.9746. We then replace world exports with the fitted value from this regression if it is less than reported output and if the fitted value is strictly positive. For observations that are still missing either output or world exports data, we replace *both* with their values lagged by one year (if available). We then keep countries for which there are at least 73 out of 119 industries. On average, the remaining countries in the data set have 94/118 industries.

Cobb-Douglas consumption shares can come from the WIOD data that give us α^j for each of the WIOD industries. We convert NACE industries to ISIC industries by assuming that each ISIC industry's Cobb-Douglas cost share is equal to the NACE consumption share times the share of the NACE industry output accounted for by the ISIC industry within it.

The UN INDSTAT data base contains data on output, value added, and total wages at the 4-digit ISIC level of aggregation and is our source for $\gamma^j_{0,n}$ and $\gamma^j_{1,n}$. Data on total labor and capital endowments come from the Penn World Tables 9.0. Next, we require empirical counterparts for $\gamma^{k,j}_n$, the Cobb-Douglas share of product k used in production of j in country n. Next we need

[42]This crosswalk is available at http://wits.worldbank.org/product_concordance.html.

input-output Cobb-Douglas shares for the countries in our data set. For this We rely on two data sets. First is the WIOD dataset which–after dropping agriculture, mining, petroleum, and services–allows us to construct a 13 by 13 IO matrix at the NACE level which roughly corresponds to the 2-digit ISIC (revision 3) level. Second we use output from the Industrial Demand-Supply Balance (IDSB) Database at the four-digit ISIC (revision 3) level and a proportionality assumption as in Trefler and Zhu (2010) to contruct the full 116 by 166 IO matrix. We discuss this in detail now.

Let j represent four digit ISIC industries and j' index the two-digit NACE level to which they belong. The WIOD data lets us observe $M^{j'k'}$ which is the total amount of good j' used in production of good k'. Define the Cobb-Douglas parameter $\gamma^{j'k'}$ as the share of the total cost of k' that accrues to j'. We want to obtain measures at the four-digit level γ^{jk}. The output side is trivial: we assume that all output industries k inherit the IO structure of the more aggregate industry k' in which they reside. This allows us to write $\gamma^{jk} = \gamma^{jk'}$ $\forall k \in k'$. To allocate shares of j' across j, we make a proportionality assumption:

$$\gamma^{jk} = \frac{Q_w^j}{\sum_{j=1}^{J} Q_w^j} \gamma^{j'k}$$

where Q_w^j is world production of good j. This is equivalent to assuming that the share of inputs provided by industry j to industry k equals the share of inputs provided by industry j' to k times the share of world output of industry j' accounted for by industry j.

Appendix C. Measuring X_{oo}^j, X_{po}^j, π_{op}^j, and π_{pp}^j

From our notation in the main text, recall that X_{ni}^j is sales from i to n of good j. The empirical strategy outlined in section 4 requires some data that is not readily available. Specifically, for each industry j it requires data on sales by ordinary firms to other ordinary firms X_{oo}^j, sales by ordinary firms to processing firms X_{po}^j, sales by processing firms to ordinary firms X_{op}^j, and sales by processing firms to other processing firms X_{pp}^j. I discuss a method to obtain these data that relies on a combination of data identities, input-output data, and identifying restrictions.

In the notation below a subscript c is for China and is the aggregate of the ordinary and processing sectors. Y_i^j represents total production of j by i, and (with a slight abuse of notation) X_{ni}^j represents total sales of j by i to n. Starting with data identities we obtain expressions where total Chinese production is the sum of ordinary and processing production, and the total value of production equals the sum of sales to each destination:

$$Y_c^j = Y_o^j + Y_p^j$$

$$Y_o^j = \sum_{n=1}^{N} X_{no}^j + X_{oo}^j + X_{po}^j$$

$$Y_p^j = \sum_{n=1}^{N} X_{np}^j + X_{op}^j + X_{pp}^j.$$

With J industries, after exploiting the trade data X^j_{no} and X^j_{np}, this gives us $3J$ equations and $6J$ unknowns : Y^j_o, Y^j_p, X^j_{no}, X^j_{oo}, X^j_{po}, X^j_{op}, X^j_{pp} for each j. Because processing firms are not allowed to sell to ordinary firms, X^j_{op}=0. I also assume that processing firms cannot sell to other processing firms such that X^j_{pp}=0. The first is a legal restriction, the second is an identifying assumption.[43] This gives the following system of equations:

$$Y^j_c = Y^j_o + Y^j_p$$

$$Y^j_o = \sum_{n=1}^{N} X^j_{no} + X^j_{oo} + X^j_{po}$$

$$Y^j_p = \sum_{n=1}^{N} X^j_{np}.$$

Now processing production Y^j_p can be measured by total processing exports $\sum_{n=1}^{N} X^j_{np}$, and ordinary production Y^j_o can be measured as the difference between total production Y^j_c and processing production Y^j_p. This brings us down to one equation and two unknowns for each j, X^j_{oo} and X^j_{po}:

$$Y^j_o - \sum_{n=1}^{N} X^j_{no} = X^j_{oo} + X^j_{po}$$

where we need to decompose total domestic ordinary production into sales to other ordinary firms X^j_{oo} and sales to processing firms X^j_{po}.

The final step in this decomposition starts by using

$$\frac{X^j_{po}}{X^j_{oo}} = \frac{X^j_p/\Phi^j_p}{X^j_o/\Phi^j_o} \tag{A6}$$

where

$$\Phi^j_p = \lambda^j_o \left(c^j_o \kappa^j_{po}\right)^{-\theta^j} + \sum_{i'=1}^{N} \lambda^j_{i'} \left(c^j_{i'} \kappa^j_{pi'}\right)^{-\theta^j} \qquad \Phi^j_o = \lambda^j_o \left(c^j_o \kappa^j_{oo}\right)^{-\theta^j} + \sum_{i'=1}^{N} \lambda^j_{i'} \left(c^j_{i'} \kappa^j_{oi'}\right)^{-\theta^j}.$$

The fact that unit costs of delivery of ordinary goods to both the ordinary and processing sector are identical allows for this expression. Similarly, where W represents the sum of all non-China countries in the world, we can write

$$\frac{X^j_{pW}}{X^j_{oW}} = \frac{\sum_{i=1}^{N} \lambda^j_i \left(c^j_i \kappa^j_{pi}\right)^{-\theta^j}}{\sum_{i=1}^{N} \lambda^j_i \left(c^j_i \kappa^j_{oi}\right)^{-\theta^j}} \frac{X^j_p/\Phi^j_p}{X^j_o/\Phi^j_o} \tag{A7}$$

[43]The latter is not fully true because we know that processing firms *can* sell to other processing firms but I assume that this is small enough to be safely assumed to be zero.

Simple manipulation and the fact that $\frac{\kappa^j_{pi}}{\kappa^j_{oi}} = (1+\tau^j_{ci})^{-1}$ allows us to write

$$\frac{X^j_{pW}}{X^j_{oW}} = \left[\frac{\sum_{i=1}^N (1+\tau^j_{ci})^{\theta^j} X^j_{oi}}{\sum_{i=1}^N X^j_{oi}}\right] \frac{X^j_p/\Phi^j_p}{X^j_o/\Phi^j_o}. \tag{A8}$$

Combining equations (A9) and (A8), we can obtain

$$\frac{X^j_{po}}{X^j_{oo}} = \frac{X^j_{pW}}{X^j_{oW}} \left[\frac{\sum_{i=1}^N (1+\tau^j_{ci})^{\theta^j} X^j_{oi}}{\sum_{i=1}^N X^j_{oi}}\right]^{-1} \tag{A9}$$

The relative domestic shipments of ordinary production to processing and ordinary firms in China $\frac{X^j_{po}}{X^j_{oo}}$ is a function of external shipments into those two sectors in a given industry as well as a weighted average of tariffs where weights correspond to the size of imports from a the country i against whom a tariff τ^j_{oi} is imposed. Intuitively, domestic shipments in China should be more skewed towards processing when the market size is larger (the first term) or when higher average tariffs make those industries less competitive (the second term).

Appendix D. Solution Algorithm

To simply the illustration, we introduce the new notation $\kappa^j_{ni} = t^j_i \tilde{\kappa}^j_{ni}$. By definition $\tilde{\kappa}^j_{ni} = (1+\tau^j_{ni})(d^j_{ni})^{\beta_j}$. With parameters θ_j, ν, $\gamma^j_{0,n}$, $\gamma^j_{1,n}$, γ^{jk}_n, α^j, L_n and K_n, and estimates of $\tilde{\lambda}^j_n \equiv \frac{\lambda^j_i}{\lambda^j_{us}}$, $\tilde{\kappa}_{ni}$, $\frac{t^j_i}{t^j_{us}}$ $(i = 1,...,N)$ and $(\lambda_{us})^{-\frac{\nu}{\theta_j}} \frac{t^j_c}{t^j_{us}}$, we can solve the model using the following solution algorithm:

(1) Guess $\{(w_n/w_{us}),(r_n/r_{us})\}^{N,c}_{n=1}$.

- Solve relative prices $\frac{P^j_n}{P^j_{us}}$ and variable production costs $\tilde{c}^j_n \equiv \frac{c^j_n}{c^j_{us}}$ from the following equations:

$$\tilde{c}^j_n \equiv \frac{\Upsilon^j_n}{\Upsilon^j_{us}} \left(\frac{w_n}{w_{us}}\right)^{\tilde{\gamma}^j_{0,n}} \left(\frac{r_n}{r_{us}}\right)^{\tilde{\gamma}^j_{1,n}} \Pi^{J+1}_{k=1} \left[\frac{p^k_n}{p^k_{us}}\right]^{\gamma^{kj}} \quad \text{for all } n = 1,...,N,o \text{ and } j$$

For $j = 1,\ldots,J$,

$$
\begin{cases}
\dfrac{p_n^j}{p_{us}^j} = \left[\dfrac{\left((\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{-\frac{\theta_j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{-\frac{\theta_j}{1-\nu}} \right)^{1-\nu} + \sum_{i=1}^N \tilde{\lambda}_i^j \left(\tilde{c}_i^j \kappa_{ni}^j\right)^{-\theta_j}}{\left((\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{us,o}^j\right)^{-\frac{\theta_j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{us,p}^j\right)^{-\frac{\theta_j}{1-\nu}} \right)^{1-\nu} + \sum_{i=1}^N \tilde{\lambda}_i^j \left(\tilde{c}_i^j\right)^{-\theta_j}} \right]^{-\frac{1}{\theta_j}} \quad \forall n \neq o,p \\
\dfrac{p_o^j}{p_{us}^j} = \left[\dfrac{(\tilde{\lambda}_o^j)\left(\tilde{c}_o^j \kappa_{oo}^j\right)^{-\theta_j} + \sum_{i=1}^N \tilde{\lambda}_i^j \left(\tilde{c}_i^j \kappa_{oi}^j\right)^{-\theta_j}}{\left((\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{us,o}^j\right)^{-\frac{\theta_j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{us,p}^j\right)^{-\frac{\theta_j}{1-\nu}} \right)^{1-\nu} + \sum_{i=1}^N \tilde{\lambda}_i^j \left(\tilde{c}_i^j \kappa_{us,i}^j\right)^{-\theta_j}} \right]^{-\frac{1}{\theta_j}} \\
\dfrac{p_p^j}{p_{us}^j} = \left[\dfrac{(\tilde{\lambda}_o^j)\left(\tilde{c}_o^j \kappa_{po}^j\right)^{-\theta_j} + \sum_{i=1}^N \tilde{\lambda}_i^j \left(\tilde{c}_i^j \kappa_{pi}^j\right)^{-\theta_j}}{\left((\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{us,o}^j\right)^{-\frac{\theta_j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{us,p}^j\right)^{-\frac{\theta_j}{1-\nu}} \right)^{1-\nu} + \sum_{i=1}^N \tilde{\lambda}_i^j \left(\tilde{c}_i^j \kappa_{us,i}^j\right)^{-\theta_j}} \right]^{-\frac{1}{\theta_j}}
\end{cases}
$$

For $j = J + 1$,

$$
\begin{cases}
\dfrac{p_n^{J+1}}{p_{us}^{J+1}} = \left[\lambda_{n,us}^{J+1} \left(\tilde{c}_n^{J+1}\right)^{-\theta^{J+1}} \right]^{-\frac{1}{\theta^{J+1}}} \quad \forall n \neq o,p \\
\dfrac{p_o^{J+1}}{p_{us}^{J+1}} = \dfrac{p_p^{J+1}}{p_{us}^{J+1}} = \left[\lambda_{o,us}^{J+1} \left(\tilde{c}_o^{J+1}\right)^{-\theta^{J+1}} \right]^{-\frac{1}{\theta^{J+1}}}
\end{cases}
$$

- Compute the expenditure on different goods as follows: for any country $n \neq o,p$

$$
\begin{cases}
\pi_{ni}^j = \dfrac{\tilde{\lambda}_i^j (\tilde{c}_i^j \kappa_{ni}^j)^{-\theta^j}}{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}} \right]^{1-\nu} + \sum_{i'=1}^N \tilde{\lambda}_{i'}^j \left(\tilde{c}_{i'}^j \kappa_{ni'}^j\right)^{-\theta^j}} \quad \forall n \neq o,p \\
\pi_{no}^j = \dfrac{(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{-\frac{\theta^j}{1-\nu}}}{(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}}} \dfrac{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}} \right]^{1-\nu}}{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}} \right]^{1-\nu} + \sum_{i'=1}^N \tilde{\lambda}_{i'}^j \left(\tilde{c}_{i'}^j \kappa_{ni'}^j\right)^{-\theta^j}} \\
\pi_{np}^j = \dfrac{(\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{-\frac{\theta^j}{1-\nu}}}{(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}}} \dfrac{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}} \right]^{1-\nu}}{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_o^j \kappa_{no}^j\right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(\tilde{c}_p^j \kappa_{np}^j\right)^{\frac{-\theta^j}{1-\nu}} \right]^{1-\nu} + \sum_{i'=1}^N \tilde{\lambda}_{i'}^j \left(\tilde{c}_{i'}^j \kappa_{ni'}^j\right)^{-\theta^j}}
\end{cases}
$$

For $n = o$,

$$
\begin{cases}
\pi_{oi}^j = \dfrac{\tilde{\lambda}_i^j (\tilde{c}_i^j \kappa_{oi}^j)^{-\theta^j}}{\tilde{\lambda}_o^j \left(\tilde{c}_o^j \kappa_{oo}^j\right)^{-\theta^j} + \sum_{i'=1}^N \tilde{\lambda}_{i'}^j \left(\tilde{c}_{i'}^j \kappa_{oi'}^j\right)^{-\theta^j}} \quad \forall i \neq o,p \text{ and } j \\
\pi_{oo}^j = \dfrac{\tilde{\lambda}_o^j (\tilde{c}_o^j \kappa_{oo}^j)^{-\theta^j}}{\tilde{\lambda}_o^j \left(\tilde{c}_o^j \kappa_{oo}^j\right)^{-\theta^j} + \sum_{i'=1}^N \tilde{\lambda}_{i'}^j \left(\tilde{c}_{i'}^j \kappa_{oi'}^j\right)^{-\theta^j}} \quad \forall j \\
\pi_{op}^j = 0 \quad \forall j
\end{cases}
$$

For $n = p$,

$$\begin{cases} \pi_{pi}^j = \frac{\tilde{\lambda}_i^j (\tilde{c}_i^j \kappa_{pi}^j)^{-\theta^j}}{\tilde{\lambda}_o^j \left(\tilde{c}_o^j \kappa_{po}^j\right)^{-\theta^j} + \sum_{i'=1}^N \tilde{\lambda}_{i'}^j \left(\tilde{c}_{i'}^j \kappa_{pi'}^j\right)^{-\theta^j}} & \forall i \neq o,p \text{ and } j \\ \pi_{po}^j = \frac{\tilde{\lambda}_o^j (\tilde{c}_o^j \kappa_{po}^j)^{-\theta^j}}{\tilde{\lambda}_o^j \left(\tilde{c}_o^j \kappa_{po}^j\right)^{-\theta^j} + \sum_{i'=1}^N \tilde{\lambda}_{i'}^j \left(\tilde{c}_{i'}^j \kappa_{pi'}^j\right)^{-\theta^j}} & \forall j \\ \pi_{pp}^j = 0 \quad \forall j \end{cases}$$

- Solve total demand from the following equations: for $n \neq o,p$,

$$X_n^j = \alpha_n^j \left(w_n L_n + r_n K_n + \sum_{j=1}^{J+1} \sum_{i=1}^{N+2} \tau_{ni}^j X_n^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j} \right) + \sum_{k=1}^{J+1} \gamma_n^{jk} \sum_{i=1}^{N+2} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k} \quad \forall j$$

For $n = o$,q

$$X_o^j = \alpha_o^j \left(w_c L_c + r_c K_c + \sum_{j=1}^{J+1} \sum_{i=1}^{N+1} \tau_{oi}^j X_o^j \frac{\pi_{oi}^j}{1+\tau_{oi}^j} \right) + \sum_{k=1}^{J+1} \gamma_o^{jk} \sum_{i=1}^{N+2} X_i^k \frac{\pi_{io}^k}{1+\tau_{io}^k} \quad \forall j$$

For $n = p$,

$$X_p^j = \sum_{k=1}^{J+1} \gamma_p^{jk} \sum_{i=1}^{N} X_i^k \frac{\pi_{ip}^k}{1+\tau_{ip}^k} \quad \forall j$$

(2) Update $\{(w_n/w_{us})',(r_n/r_{us})'\}_{n=1}^{N,c}$ with the labor and capital clearing conditions:

$$\begin{cases} \sum_{j=1}^{J+1} \gamma_{0n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{\tilde{\tau}_{in}^j} = w_n' L_n & \text{if } n \neq c \\ \sum_{j=1}^{J+1} \gamma_{0o}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{\tilde{\tau}_{io}^j} + \sum_{j=1}^{J} \gamma_{0p}^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{\tilde{\tau}_{ip}^j} = w_c' L_c & \text{if } n = c \end{cases}$$

and

$$\begin{cases} \sum_{j=1}^{J+1} \gamma_{1n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{\tilde{\tau}_{in}^j} = r_n' K_n & \text{if } n \neq c \\ \sum_{j=1}^{J+1} \gamma_{1o}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{\tilde{\tau}_{io}^j} + \sum_{j=1}^{J} \gamma_{1p}^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{\tilde{\tau}_{ip}^j} = r_c' K_c & \text{if } n = c \end{cases}$$

(3) Repeat the above procedures until $\{(w_n/w_{us})',(r_n/r_{us})'\}_{n=1}^{N,c}$ is close enough to $\{(w_n/w_{us}),(r_n/r_{us})\}_{n=1}^{N,c}$.