Is Processing Good?: Theory and Evidence from China *

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ABSTRACT:

Policies encouraging processing trade are common in developing countries and are thought to encourage integration into global markets. Agents engaged in processing production import duty free but are not allowed to sell the resulting output on the domestic market. For ordinary production, the reverse holds: imports are subject to tariffs but domestic sales are allowed. This paper studies the welfare effects of these policies using Chinese data for 109 industries for 2000-2007. Counterfactual policy experiments imply large welfare losses ($\approx 10\%$ to 14%) 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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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 agents to engage in processing.[1] Under this regime, agents import intermediate goods duty free circumventing tariffs. However, the resulting output is rarely–if ever–allowed to be sold on the domestic market. Agents 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. Radelet and Sachs (1997) argue that programs encouraging processing trade have been instrumental in the successful economic development of East and Southeast Asia. While processing regimes offer the potential of increased labor demand, they often disallow domestic consumers of final goods or intermediate inputs from benefiting from lower prices. Despite the existence of many papers analyzing processing regimes, there have been very few quantitative cost-benefit analyses.[2]

This paper conducts such an analysis by examining the welfare implications of China's processing regime for the years 2000 through 2007.[3] 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

[1] In this paper, unless describing specific data or prior results, we refer to "producers" or "agents" instead of "firms." As shown in Manova and Yu (2016) and Brandt and Morrow (2017), there are many firms that engage in both processing and ordinary production with organizational forms usually determined at the product and not the firm level.

[2] e.g. Madani (1999), OECD (2007) offer descriptive analysis of processing but do not engage in formal cost-benefit analysis. Panagariya (1992) derives analytical welfare results in a small open economy three country setting. Ianchovichina (2007) and Connolly and Yi (2015) assess the welfare effects of tariff drawbacks for China and Korea, respectively. However, both assume that all exports receive drawbacks and therefore do not explore the endogenous choice of how to organize into ordinary or processing production. In addition, neither explore the welfare losses from not allowing agents engaged in processing to sell domestically.

[3] 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 former represents more than 75 percent. Both forms allow for duty free imports, 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, most notably 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).

(2015), and Levchenko and Zhang (2016).

The paper has two goals. First, we document the trajectories of TFP for ordinary and processing production during the years 2000-2007. This allows us to assess potential differences in productivity between the two organizational forms, and if such differences are essential for understanding the potential gains allowing processing output to be sold domestically. Second, we conduct a series of counterfactual experiments that assess the welfare effects of processing. The first experiment assesses the welfare gains of the tariff exemption for processing by comparing the welfare associated with the observed equilibrium with one in which processing faces import tariffs. The second experiment calculates welfare in an equilibrium which agents engaged in processing are allowed to sell to domestic agents without any restriction.

We emphasize three results. First, although ordinary production is slightly more productive on average, there are substantial differences in the gap in measured productivity between the two organizational forms across industries in a given year. The productivity premium of processing relative to ordinary production ranges from -19% to +11% in 2000. This heterogeneity suggests that looking at a single premium estimated over all industries may be misleading.

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

Third, we find that there are substantial welfare *losses* for Chinese agents associated with not being able to buy final goods and intermediate inputs from processing. We estimate that the real wage for a representative agent in China in 2000 would have been approximately 14% higher in a world in which processing could sell to domestic agents. The increase in real income would have been smaller ($\approx 10\%$) due to a loss of tariff income as increased processing sales would crowd out imports.[4] We also show that this result is not due to their duty-free status but rather to their ability to offer different menus of prices to domestic consumers and downstream producers.

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

Our finding of relatively large gains from allowing processing to sell domestically comes from two aspects of our model: i) Differences in fundamental productivity levels and the imperfect correlation of idiosyncratic draws across the two organizational forms, and ii) international trade costs.[5]

Our modelling framework allows–but does not impose–an imperfect correlation of productivity draws between ordinary and processing production within an industry. 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 at the industry level. Despite the fact that this parameter has generally been non-identified in the literature, we introduce a method to estimate its value combining the insights of Berry (1994) with the triad approach of Caliendo and Parro (2015).[6] It is key for our results that we find that, while draws are correlated, the correlation is far from perfect.

Allowing processing to sell domestically is potentially more powerful than international trade liberalization due to the presence of large documented barriers to international trade. Because domestic production has no such trade costs, endogenous expenditure shares for these goods are higher, and falling prices for domestically produced goods will have relatively larger effects on the overall price index.[7] This finding of the importance of domestic market liberalization for welfare links this paper to other papers that find large welfare effects of reducing barriers to domestic trade and migration (e.g. Atkin and Donaldson (2015) and Tombe and Zhu (2015)).

[5]As we discuss later, we use "fundamental productivity" to represent the location of Frechét productivity distributions and "correlation" to discuss the correlation of idiosyncratic draws across groups of producers.

[6]Lind and Ramondo (2018) independently establishes a two-step gravity-based procedure to measure this correlation across countries and is therefore a notable exception.

[7]Variable mark-ups introduce the possibility of lower price charged domestic producers due to increased import competition. However, as shown in Arkolakis, Costinot, Donaldson and Rodríguez-Clare (2015), foreign producers might increase their mark-ups in response offsetting some or all of the gains from lower mark-ups charged by domestic producers. Relatedly, Defever and Riano (2017) explore the welfare effect of special tax treatment for processing firms using a two country-single sector model. In the context of a Melitz (2003) model, they argue that special tax treatment afforded to processing firms disincentivized entry by Chinese firms into domestic markets leading to a higher domestic price index.

While we do not explicitly model why productivity might vary between the two organization forms, we discuss potential reasons for these differences. Processing typically entails the labor-intensive assembly of products with high-import content.[8]. The high-import content often signals higher quality which is generally isomorphic to productivity. In addition, a foreign partner frequently assumes responsibility for design, management of the supply chain, and logistics. Local firms involved in processing largely oversee the labor-intensive assembly and must be able to ensure quality levels and the timely delivery of output, while keeping final costs down. On the other hand, firms involved in ordinary production typically require a much broader set of capabilities that span design, local sourcing, manufacturing, and logistics. With domestic capabilities generally lower in China than in advanced countries, product design needs to fit the capabilities of local suppliers, which typically means less sophisticated products based on slightly earlier vintage technologies. Among other factors, these differences in firms' abilities to use high quality inputs, design goods, and manage supply chains as well as the impact of these activities on measured productivity can lead to differences in productivity between ordinary and processing production.

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. Because we are explicitly interested in productivity differences between ordinary and processing trade, and their potential effect on welfare, we work in levels as in Levchenko and Zhang (2016) and not in "hat algebra" as in Caliendo and Parro (2015).

Finally, drawing upon Chinese data to explore the mechanisms at play, this paper is closely linked to a literature that assesses both the causes and consequences of China's processing regime. Although we focus on tariff treatment as emphasized in Brandt and Morrow (2017), our use of a structural model of international trade allows us to identify aggregate effects which are not identified using difference-in-difference methods. Other papers that analyze the characteristics of firms engaged in processing relative to ordinary trade include Yu (2015), Kee and Tang (2016),

[8] See Kee and Tang (2016) and Koopman, Wang and Wei (2012) for more on the import content of processing relative to ordinary exports

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.

2. Model

The model that we use for our quantitative exercise possesses several important features. First, in order to conduct quantitative experiments, it is an equilibrium model with market clearing in which all prices and quantities are endogenous. Second, because processing imports intermediate inputs in order to produce and export goods, there are rich input-output linkages. Third, because processing activities tend to be concentrated in certain industries (e.g. Brandt and Morrow (2017)), it possesses multiple industries. Finally, in order to distinguish productivity from differences in capital intensity, we allow for multiple factors of production.

We now describe the model in detail. It is a multi-country, multi-sector, multi-factor general equilibrium model in which Chinese producers engage in either ordinary or processing production. As in Brandt and Morrow (2017), we model ordinary and processing trade as follows: processing production does not face tariffs on imports but is restricted from selling on domestic (i.e. Chinese) markets. Ordinary production faces import tariffs but are free to sell on domestic markets. Those engaged in ordinary production can sell to those engaged in processing but the reverse is not allowed. In what follows, we refer to whether sales or exports go 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 countries outside China engage in ordinary trade exclusively.[9]

[9]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.

2.1 Preliminaries

In addition to China, there are N countries indexed by i. Because our model is static, we suppress the time subscript although we re-introduce it when we present our empirical work. As in Levchenko and Zhang (2016), there are J traded and one non-traded sector indexed by j,k. We model China as two additional markets: $o$rdinary (o) and $p$rocessing (p). In terms of notation, there are $N+2$ "countries" indexed with subscripts $i = 1,...,N,o,p$. 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, 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.

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 ordinary and processing in China such that we can write their factor returns as w_c and r_c.[10]

Within each (superscript) industry j, there is a continuum of varieties indexed by 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.

2.2 Demand

Preferences are identical and homothetic across countries with the representative consumer in each country n possessing the following utility function defined over $J+1$ consumption aggregates: $U_n = \Pi_{j=1}^{J+1}\left(C_n^j\right)^{\alpha^j}$.

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

2.3 *Production*

Production of any variety ω^j 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 Cobb-Douglas 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 $\gamma_{l,n}^j + \gamma_{k,n}^j + \sum_{k=1}^{J}\gamma_n^{kj} = 1$. $l_n^j(\omega^j)$ 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. We allow the factor cost shares to vary across both industries and also countries within an industry. Unit cost is $c_n^j / z_n^j(\omega^j)$ 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-country specific constant.[11] p_n^k is the price of a composite unit of k in country n as we discuss shortly.

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 intermediate goods ω^j from the lowest cost supplier. This composite is used for intermediate inputs for downstream production as well as final goods in consumption. The market clearing condition for the composite intermediate good in sector j in country n (including ordinary) is therefore $Q_n^j = C_n^j + \sum_{k=1}^{J+1}\int m_n^{jk}(\omega^k)d\omega^k$. For processing, goods market clearing is given by $Q_p^j = \sum_{k=1}^{J}\int m_p^{jk}(\omega^k)d\omega^k$; all of the composite processing output must be used in the production of processing goods and none can be used to satisfy final demand.[12]

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

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

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

provider of the variety in some market. Transport costs and tariffs imply that even if 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 former 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 into iceberg trade costs. We assume that 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), 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. Finally, define ad-valorem tariffs $(1+\tau_{ni}^j)$ where τ_{ni}^j is the statutory tariff that n imposes on varieties of 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 $\tau_{io}^j = \tau_{ip}^j$. The total per-unit cost of shipping a unit of a variety of j from i to n, κ_{ni}^j takes the following multiplicative form:

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

With perfect competition, the equilibrium price of ω^j in country n, $p_n^j(\omega^j)$, is 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 $g^j(d_{nn}) = 1$ and $t_n^j = 1$ for domestic shipments.

2.5 *Productivity Distributions*

Ricardian motives for trade follow Eaton and Kortum (2002) and Costinot et al. (2012). Outside of China, those 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. First, there is no reason to assume that draws between the two organizational forms are independent and, second, it is not obvious that draws should be correlated or that they are taken from the 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 a multivariate Frechét distibution:

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

where $\nu \in [0,1)$ 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 ($\nu \to 0$), heterogeneity in productivity across ordinary and processing increases, leading to larger potential gains from buying from both forms of production relative to buying from only one. As the correlation increases ($\nu \to 1$), the draws are more correlated and there are smaller gains from buying from both forms of production instead of only one.[13]

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. For sales by non-China sources into destinations outside of China, 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 in China requires slightly more care. The share of expenditure on sector j goods in

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

destination n accruing to ordinary production in China is given by

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

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 relatively larger, the relative cost of ordinary trade c_o^j/c_p^j is lower, or iceberg costs confer an advantage to ordinary trade $\kappa_{no}^j < \kappa_{np}^j$.[14] Similarly, the expenditure share accruing to processing is

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

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 the restriction that processing cannot sell to those organized into ordinary production, and $\kappa_{pp}^j = \infty$ imposes the condition that processing cannot sell to itself.[15] This allows us to derive a share of expenditure by processing accruing to country i as

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

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

[15]We make the assumption that processing production sources from ordinary production but not from itself for two reasons. 1. Legally, processing output is required to leave the country. While there are exemptions for selling to other processing producers, we believe the volume of these sales at the industry level is negligible. 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. Empirically, we find that exporting firms that engage in processing obtain on average 93% of their total revenue from exporting and that the median firm obtains all of their revenue from exporting. Aggregating up to the industry level, 97% of total sales for these firms comes from exporting while the median is 96%.

where Φ_p^j is given by setting $n = p$ and $\kappa_{pp} = \infty$ in equation (5). The share of expenditures in destination o accruing to source 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 proofs.[16] Finally, as in Eaton and Kortum (2002), price distributions are give by:

$$p_n^j = A^j \left[\Phi_n^j\right]^{-\frac{1}{\theta^j}} \tag{10}$$

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 can 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

[16] For the non-traded sector, $\pi_{nn}^{J+1} = 1$ and $\pi_{ni}^{J+1} = 0$ if $i \neq n$.

intermediate input for domestic final sales:

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

Income is 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 the representative agent: $R_n \equiv \sum_{j=1}^{J} \sum_{i=1}^{N+2} \tau_{ni}^j M_{ni}^j$ 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:

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

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:

$$\sum_{j=1}^{J+1} \gamma_{l,n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} = w_n L_n \qquad \text{and} \qquad \sum_{j=1}^{J+1} \gamma_{k,n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} = r_n K_n. \tag{16}$$

For China, these expressions are

$$\sum_{j=1}^{J+1} \gamma_{l,o}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{1+\tau_{io}^j} + \sum_{j=1}^{J} \gamma_{l,p}^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{1+\tau_{ip}^j} = w_c L_c \tag{17}$$

and

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

2.9 Equilibrium

Definition 1 *Given L_n, K_n, λ_n^j, $g^j(d_{ni})$ 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 $\{\tau_{ni}^j\}$ 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), (17) *and* (18) *for all k,i.*

3. Data

The Data Appendix discusses our data set in detail, and here we briefly discuss aspects of it. 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 come from the BACI data base maintained by CEPII.[17] Chinese Trade data come from the Customs Administration of China. Because trade data do not track domestic shipments, we take nominal output data from the UN IDSB data base and subtract exports to obtain domestic shipments. For China, total production comes from the Annual Survey of Manufacturers from the National Bureau of statistics. We subtract exports from the Customs Administration to obtain domestic sales.[18] All remaining data used in estimation of the gravity model come from CEPII (distance and contiguity measures) or UN TRAINS (tariff data). Total employment and the (real) capital stock both come from the Penn World Tables 9.0

The cost share of labor $\gamma^j_{l,n}$ is the share of total output paid to labor in the UN INDSTAT data set for manufacturing and WIOD for the non-traded sector. The share of intermediate inputs is given by one minus the total share of value added in output. These vary by both country and industry. Capital's share of output in an industry $\gamma^j_{k,n}$ is one minus labor's share minus the share of intermediate inputs. For China, these statistics are derived from the Annual Survey of Manufacterers. We calculate γ^{jk}_n 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 a proportionality assumption, we create ISIC specific intermediate input shares, $\tilde{\gamma}^{jk}$. We then multiply these by one minus the value added share (which varies across countries) to create γ^{jk}_n. The Data Appendix describes this in detail.

[17]These data are aggregated from the HS six-digit level to the four-digit ISIC level.

[18]These data do not distinguish whether sales by Chinese firms are to ordinary or to processing firms (processing firms do not sell domestically). Appendix C shows how we can use the structure of the model to allocate domestic sales into sales to other ordinary producers/consumers and to processing producers.

4. Mapping Theory onto Empirics

4.1 *Estimates of* θ^j *and* ν.

As in Simonovska and Waugh (2014), we use $\theta^j = 4 \ \forall j$.[19] Because estimates for ν do not exist, we offer a new strategy here to estimate its value. We start by taking a stand on the correlation structure of productivity draws. First, as in much of the literature, we assume that productivity draws across countries in a given industry are independent. However, we allow for productivity draws across ordinary and processing production in an industry to be correlated. Then, using same triad strategy as Caliendo and Parro (2015), we can obtain the following expression:

$$\left(\frac{\pi^j_{no}\pi^j_{oh}\pi^j_{hn}}{\pi^j_{nh}\pi^j_{ho}\pi^j_{on}}\right) = \left(\frac{(1+\tau^j_{no})(1+\tau^j_{oh})(1+\tau^j_{hn})}{(1+\tau^j_{nh})(1+\tau^j_{ho})(1+\tau^j_{on})}\right)^{-\theta^j} \left(\frac{s^j_{no}}{s^j_{ho}}\right)^{\nu}. \tag{19}$$

Conditional on θ^j, we can use a simple method of moments estimator to obtain a value of ν. This procedure is still valid when tariffs are set at most favored nation (MFN) rates. In the extreme case where all tariffs are equal across all country pairs, ν is still identified and equation (19) becomes

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

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)), ordinary and processing processing trade to reside within a group. 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 and leads to a stronger relationship between the within-group share on the right hand side and ordinary market shares on the left hand side. This is analogous to techniques developed in Berry (1994) in which across-group market shares are regressed on within-group 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

[19] We also set $\sigma^j = 2 \ \forall j$. This does not affect our results as in Eaton and Kortum (2002).

correlation parameter in a multi-variate Frechét distribution.[20] 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:

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

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.[21] 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, which produces an estimate of 0.64.[22] Using a lower value of $\widehat{\nu}$ reduces 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.[23]

[20] 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 which countries reside in which groups. However, if a researcher is willing to take a stand on what are the 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. Calibration based estimates of this correlation parameter are found in Arkolakis, Ramondo, Rodríguez-Clare and Yeaple (2013) and Lagakos and Waugh (2013). Independently of this paper, Lind and Ramondo (2018) develop a two-step gravity-based estimator to estimate a single correlation parameter but do not develop within- or across- group differences in this parameter.

[21] Unlike Caliendo and Parro (2015), we move the term involving θ^j over to the left hand side. We do this for two reasons. First, we wish to link our results to the existing literature and, for comparability sake, we choose to use a common value for θ^j. Second, and more importantly, by 2000, much of the variation in tariffs across countries had disappeared as WTO membership for many countries led to MFN tariff rates. This removes valuable variation that was present prior to WTO (the period of Caliendo and Parro's analysis). In our data at the exporter-importer-ISIC industry year level in 2000, 80% of reported (simple average) tariffs were set at the MFN rate. At the same level, the correlation between average tariffs and MFN tariffs is 0.97; a regression of the average tariff on the MFN tariff delivers a coefficient of 0.97 and a $R^2 = 0.96$. This does not mean that tariff cuts can not matter but it does mean that the triad approach removes much of the meaningful variation post WTO.

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

[23] Looking across countries, Lind and Ramondo (2018) estimate a lower correlation parameter: 0.31. This is consistent with a hypothesis that productivity draws are more correlated within a country than across countries.

4.2 *Measuring* $\lambda_n^j/\lambda_{us}^j$

Each counterfactual requires empirical counterparts for $\lambda_n^j/\lambda_{us}^j$, $\widehat{\lambda_n^j/\lambda_{us}^j}$. To obtain these, we follow the structural gravity approach of Levchenko and Zhang (2016). This procedure first involves estimating a gravity model for each industry and year. As we discuss next, country-industry fixed effects embody differences in unit costs comprising differences in TFP, factor prices, and intermediate input prices. Because factor prices are available in the data described in section 3, and intermediate input prices can be obtained using the structure of the model, we can isolate $\lambda_n^j/\lambda_{us}^j$. We first show how to solve for the state of technology, $\lambda_n^j/\lambda_{us}^j$, outside of China, and then in the ordinary sector of China. We then discuss the additional considerations needed when solving for $\lambda_p^j/\lambda_{us}^j$.

4.21 $\lambda_n^j/\lambda_{us}^j$ *outside of China and for Ordinary Trade*

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

$$\ln\left(\frac{\pi_{ni}^j}{\pi_{nn}^j}\right) = \ln\left(\lambda_i^j\left[c_i^j\right]^{-\theta^j}\right) - \ln\left(\lambda_n^j\left[c_n^j\right]^{-\theta^j}\right) - \theta^j \ln\left(\kappa_{ni}^j\right). \tag{20}$$

The first two terms represent the effect of differences in average unit costs between n and i, and the last term reflects international trade costs. We parameterize iceberg costs as in Eaton and Kortum (2002), Waugh (2010), and Levchenko and Zhang (2016): $\ln\left(\kappa_{ni}^j\right) = \theta^j \ln(1+\tau_{ni}^j) + \sum_{d=1}^{6}\beta_d^j d_{ni,d} + b_{ni}^j + \delta_i^{j,x} + \epsilon_{ni}^j$ 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.[24] β_d^j is the industry-specific effect of being in interval d. b_{ni}^j is the industry-level effect of *not* sharing a border. When i is other than China, $\delta_i^{j,x} \equiv \ln(t_i^j)$. For $i = o$ and $i = p$, respectively,

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

[24] $\delta_i^{j,x}$ is a dummy variable that turns on when i is an exporting country for industry j. Intervals are in miles: [0,375); [375,750); [750,1500); [1500,3000); [3000,6000); and [6000,maximum].

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

The extra terms for China reflect the correlated Frechét draws.[25]

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

$$\ln\left(\frac{\pi_{ni}^j}{\pi_{nn}^j}\right) + \theta^j ln(1+\tau_{ni}^j) = \delta_i^j - \delta_n^j + \sum_{d=1}^{6}\beta_d^j d_{ni,d} + b_{ni}^j + \delta_i^{j,x} + \epsilon_{ni}^j \tag{21}$$

where ϵ_{ni}^j is an error term that is assumed to have the usual i.i.d. properties.

With $\widehat{\delta}_n^j$ in hand, we can exponentiate the ratio, $\widehat{\delta}_i^j/\widehat{\delta}_{us}^j$ and use equation (1) to obtain

$$exp\left(\frac{\widehat{\delta}_i^j}{\widehat{\delta}_{us}^j}\right) = \frac{\lambda_i^j}{\lambda_{us}^j}\left(\frac{c_i^j}{c_{us}^j}\right)^{-\theta^j} \tag{22}$$

At this point, it is typical to assume common factor cost shares across countries within an industry, such that c_i^j/c_{us}^j is a function of relative input prices and industry-specific common Cobb-Douglas factor shares across countries α_l^j,α_k^j.[26] This allows recovery of estimates of $\lambda_i^j/\lambda_{us}^j$. 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 allow for more general production functions that are well-approximated by the translog function. This allows us to write (22) as

$$exp\left(\frac{\widehat{\delta}_i^j}{\widehat{\delta}_{us}^j}\right) = \frac{\lambda_i^j}{\lambda_{us}^j}\left[\left(\frac{w_i}{w_{us}}\right)^{\tilde{\gamma}_{l,i}^j}\left(\frac{r_i}{r_{us}}\right)^{\tilde{\gamma}_{k,i}^j}\Pi_{k=1}^{J+1}\left(\frac{p_i^k}{p_{us}^k}\right)^{\tilde{\gamma}_i^{kj}}\right]^{-\theta^j} \tag{23}$$

where $\tilde{\gamma}_{l,i}^j \equiv \frac{\gamma_{l,i}^j+\gamma_{l,us}^j}{2}$. $\tilde{\gamma}_{k,i}^j$ and $\tilde{\gamma}_i^{kj}$ are defined analogously.[27] While this calculation is general up to a translog approximation, when we move to our counterfactual analyses, we assume that factor

[25]Because ordinary and processing trade only compete on external markets due to the prohibition on domestic sales for processing, they show up in the exporting effect and disappear when the correlation between draws goes to zero (i.e. $\nu = 0$). These extra terms are are analogous to the extra price index that appears in two-tier CES utility functions as in Bombardini, Kurz and Morrow (2012).

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

[27]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.

cost shares are invariant to equilibrium factor prices (i.e. that production is Cobb-Douglas with country-industry specific factor shares). In this sense our counterfactuals calculations rely on more restrictive assumptions than our productivity calculations.

Equation (23) 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 estimates of $\frac{\lambda_i^j}{\lambda_{us}^j}$. Data on w_i, r_i, $\gamma_{l,n}^j$, $\gamma_{k,n}^j$, and γ_n^{jk} are described in section 3, and, following Simonovska and Waugh (2014), we use a constant value of $\theta = 4$ for θ^j. This leaves us requiring empirical counterparts of $\frac{p_n^k}{p_{us}^k}$ to obtain empirical counterparts of $\frac{\lambda_i^j}{\lambda_{us}^j}$ which we obtain following Shikher (2012) and Levchenko and Zhang (2016).[28]

4.22 *Obtaining Values of $\lambda_p^j / \lambda_{us}^j$*

Obtaining productivity for processing in China requires a little more work. Since π_{pp}^j=0, equation (21) is undefined when processing is the destination location, and shipments for processing only show up as exports. Consequently, any industry-specific fixed effect for processing only identifies the combination of unit cost and the industry-specific exporting cost. We refer to this composite as

[28] To obtain these, take the ratio of π_{ii}^j and $\pi_{us,us}^j$, and equation (10) to obtain: $\frac{\pi_{ii}^j}{\pi_{us,us}^j} = \left(\frac{p_i^j}{p_{us}^j}\right)^{\theta^j} \frac{\lambda_i^j \left(c_i^j\right)^{-\theta^j}}{\lambda_{us}^j \left(c_{us}^j\right)^{-\theta^j}}$. This can easily be manipulated using equation (23) to obtain the empirical counterpart of p_n^k / p_{us}^k, $\widehat{p_n^k / p_{us}^k}$, in terms of data, $\frac{\pi_{ii}^j}{\pi_{us,us}^j}$, and previously estimated values $\frac{\widehat{\delta}_i^j}{\widehat{\delta}_{us}^j}$: $\widehat{\left(\frac{p_i^j}{p_{us}^j}\right)^{\theta^j}} = \frac{\frac{\pi_{ii}^j}{\pi_{us,us}^j}}{\left[\exp\left(\frac{\hat{\delta}_i^j}{\hat{\delta}_{us}^j}\right)\right]}$. With these in hand, we can easily calculate $\Pi_{k=1}^{J+1} \left(\frac{\widehat{p}_i^k}{\widehat{p}_{us}^k}\right)^{\gamma^{kj}}$, and obtain values of $\lambda_i^j / \lambda_{us}^j$ from equation (23). To interpret total factor productivity as a cost-shifter relative to the US, our preferred measure of productivity is given by $\left(\frac{\lambda_i^j}{\lambda_{us}^j}\right)^{\frac{1}{\theta^j}}$. See Appendix D for details of how to create the price index for non-traded goods.

$\delta_p^{j,x}$.[29] If we set $t_o^j = t_p^j$ and exponentiate δ_o^j, $\delta_o^{x,j}$ and $\delta_p^{j,x}$, we can obtain obtain:

$$\frac{\exp\left(\widehat{\delta}_o^j\right)\exp\left(\widehat{\delta}_o^{j,x}\right)}{\exp\left(\widehat{\delta}_p^{j,x}\right)} = \frac{\lambda_o^j}{\lambda_p^j}\left(\frac{c_o^j}{c_p^j}\right)^{-\frac{\theta^j}{1-\nu}}. \tag{24}$$

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 $\widehat{\frac{p_p^j}{p_o^j}}$, and $\lambda_o^j/\lambda_{us}^j$ from above, we can calculate $\lambda_p^j/\lambda_{us}^j$.

5. Results

In this section, we first briefly discuss the gravity models that we estimate and our estimates of total factor productivity for both China's processing and ordinary regimes. We then explore our counterfactual exercises. We show 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 producers are large and approximately 10% of real income and 14% of real wages in 2000.[30] Finally, we assess the relative contributions of falling tariffs and rising domestic productivity in China's aggregate transition from processing to ordinary trade. Holding

[29]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.

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

productivity constant, lower statutory tariffs reduced input tariffs, and that this disincentivized agents to organize through processing. We find that that this is consistent with approximately 30% of the total change in the share of processing trade during this period. In comparison, increasing domestic productivity can explain approximately 77%. Both together can explain the entirety.[31]

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 (21) 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 .961 and .968, respectively.[32]. The mean value for the estimated coefficients on the dummy variables for distance are monotonically increasing in absolute value with values of .321, -.471, -.802, -1.489, -1.813, -1.841 for the six intervals in increasing order of distance.[33] The dummy variable that takes a value of one if the two countries do *not* share a border is negative for 105 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.

5.2 Productivity

We now examine productivity in the ordinary and processing sectors in China in 2000. These estimates are of interest on their own, but are also critical in understanding the equilibrium effect of allowing processing producers to sell domestically.

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

[32] The minimum is .875 and the maximum is .995

[33] The fact that the shortest distance is not negative is not concerning because, as in Eaton and Kortum (2002), there is no omitted distance group.

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.[34] These mixed results may be due to methodological hurdles that make comparison of TFP difficult across the two regimes. First, on the output side, output prices across ordinary and processing can be difficult to compare because of issues including quality differences and transfer pricing.[35] 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. Second, we can take into account differences in input in prices paid by ordinary and processing producers due to how imported intermediate inputs are treated.

Table 1 displays summary statistics for mean TFP measures for ordinary and processing trade relative to the US (and relative to one another) for 2000 and 2007. The first row shows that the (unweighted) average ordinary productivity in China was 39.8% of the US while productivity in processing was only slightly lower. Median productivity levels are similar. Average productivity of processing relative to ordinary production (the third row) was approximately 95%.[36] Perhaps not surprisingly, there is substantial heterogeneity around that mean with a 95% confidence interval of [-16.7%,+10.8%]. The histogram in figure 1 presents this heterogeneity.[37] Looking at the bottom

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[34] 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 using detailed data for one industry.

[35] See Brandt and Morrow (2017).

[36] 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 $\left(\widehat{\lambda}^j_{p,2000}/\widehat{\lambda}^j_{o,2000}\right)^{\frac{1}{\theta}}$.

[37] 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).

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	0.398	0.386	0.176	0.074	1.623
$\left(\widehat{\lambda}^{j}_{p,2000}\right)^{\frac{1}{\theta}}$	108	0.383	0.362	0.186	0.079	1.636
$\left(\widehat{\lambda}^{j}_{p,2000}/\widehat{\lambda}^{j}_{o,2000}\right)^{\frac{1}{\theta}}$	108	0.956	0.948	0.092	0.681	1.245
$\left(\widehat{\lambda}^{j}_{o,2007}\right)^{\frac{1}{\theta}}$	109	0.527	0.487	0.181	0.186	1.200
$\left(\widehat{\lambda}^{j}_{p,2007}\right)^{\frac{1}{\theta}}$	109	0.507	0.465	0.193	0.186	1.258
$\left(\widehat{\lambda}^{j}_{p,2007}/\widehat{\lambda}^{j}_{o,2007}\right)^{\frac{1}{\theta}}$	109	0.957	0.949	0.078	0.770	1.296

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 $\theta^{j} = 4$ for all j. All values are relative to the US.

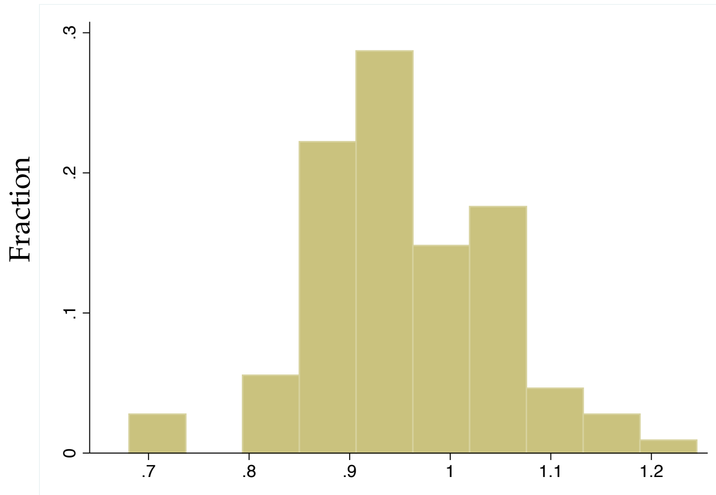
three rows, while productivity grew for each type of production (rows 4 and 5), within-sector productivity differences were unchanged on average.[38]

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 catch-up in productivity with average growth in both ordinary and processing productivity relative to the US of approximately 38% (approx. 4.1% per annum).

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 $\left(\widehat{\delta}^{j}_{o,t}\right)^{-\frac{1}{\theta^{j}}}$ and $\left(\widehat{\delta}^{j}_{p,t}\right)^{-\frac{1}{\theta^{j}}}$ and their evolution. These estimates of unit costs embody differences in productivity, prices of primary factors, and prices of intermediate inputs. If primary factors of production are mobile between ordinary and

[38]Similar results hold when allowing θ^{j} to vary as in Caliendo and Parro (2015): ordinary production is more productive in both periods on average but within-industry differences are nearly unchanged. When weighting by industry size, an advantage for processing emerges: processing for productivity in 2000 was 61% of the US level while ordinary productivity was 47%. But by 2007, there has been substantial increases in ordinary's largest sectors such that its productivity was 60% of the US while TFP processing only increased to 69% of the US level in 2007.

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 $\theta^j = 8\ \forall j$.

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

variable	N	mean	Median	sd	min	max
$\left(\lambda_{o,2007}^j/\lambda_{o,2000}^j\right)^{\frac{1}{\theta}}$	109	1.378	1.356	0.305	0.566	2.608
$\left(\lambda_{p,2007}^j/\lambda_{p,2000}^j\right)^{\frac{1}{\theta}}$	108	1.384	1.357	0.280	0.580	2.464

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 $\theta^j = 4$ for all j.

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	0.744	0.753	0.227	0.285	1.385
$\left(\frac{\widehat{\delta}^j_{p,2007}}{\widehat{\delta}^j_{p,2000}}\right)^{-\frac{1}{\theta^j}}$	108	0.809	0.777	0.305	0.259	2.103
$\left(\frac{\widehat{\delta}^j_{p,2007}\widehat{\delta}^j_{o,2000}}{\widehat{\delta}^j_{p,2000}\widehat{\delta}^j_{o,2007}}\right)^{-\frac{1}{\theta^j}}$	108	1.093	1.098	0.203	0.349	1.912

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 $\left(\widehat{\delta}^j_p\right)^{-\frac{1}{\theta^j}} \equiv \left(\widehat{\delta}^{j,x}_p / \widehat{\delta}^{j,x}_o\right)^{-\frac{1}{\theta^j}} = c^j_p / \left(\lambda^j_{p,t}\right)^{\frac{1}{\theta^j}}$. These estimates are created using the procedure described in section 4 and a value of $\theta^j = 4$ for all j. All values are relative to the US.

processing trade, all differences are due to productivity and differences in the relative 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.[39] 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 ordinary unit costs in 2007 were 74%% of their level in 2000, while for processing the number was 81%. The final row shows that on average, processing unit costs fell by 9.3% percentage points *less* than they did for ordinary during this time. Combined with our result that shows that within-industry productivity grew at similar rates (table 1 rows 3 and 6), unit costs for ordinary trade seem to have fell more than for processing because the earlier benefitted from lower input tariffs and not from different trajectories of productivity.

Combined, we emphasize two results. First, ordinary production was slightly more productive than processing, there was distinct heterogeneity 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 across all industries. Second, while changes in TFP across the two organizational forms

[39]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.

were very similar during this time, falling input tariffs caused the unit cost advantage of organizing through processing relative to ordinary to diminish.

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. Before proceeding to our counterfactual experiments, we briefly assess model fit by comparing the raw data to model-generated data using our estimated parameters to solve for a baseline equilibrium including the endogenous trade shares $\widehat{\pi}_{ni}^{j}$.[40] As suggested by the high R^2 statistics from the gravity model estimation, π_{ni}^{j} and its model generated counterpart, $\widehat{\pi}_{ni}^{j}$, are highly correlated. The correlation between the two is 0.90 and the slope coefficient from a regression of $\widehat{\pi}_{ni}^{j}$ on π_{ni}^{j} is 0.84.[41] 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. In the data the share of ordinary exports in 2000 was 60% while the model delivers 59%. Taking into consideration that this is a non-targeted moment in our estimation, this is reassuring.[42]

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.

Table 4 presents our results. The first row is not a counterfactual experiment. Instead, it is a benchmark simulation that uses $\widehat{\lambda}_{i,2000}^{j}$ and observed tariffs $\tau_{ni,2000}^{j}$. The outputs of this exercise are model-implied nominal wages, the price index, the real wage (the ratio of the nominal wage to

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

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

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

Table 4: Real Wages and Income: Counterfactual Simulations

Specification Number	**Specification Description**	**Nominal Wage (rel. to US)**	**Price Index**	**Real Wage (rel. to US)**	**Real Income (rel. to US)**
(1)	Benchmark	0.0501	0.6422	0.0780	0.1747
(2)	$\tau_{pi}^{j} = \tau_{oi}^{j}$	0.0500	0.6417	0.0779	0.1747
(3)	$\kappa_{op}^{j} = \kappa_{pp}^{j} = 1$	0.0593	0.6618	0.0895	0.1921
(4)	$\kappa_{op}^{j} = \kappa_{pp}^{j} = 1$, $\lambda_{o}^{j} = \lambda_{p}^{j}$	0.0610	0.6638	0.0920	0.1958
(5)	$\kappa_{op}^{j} = \kappa_{pp}^{j} = 1$, $\tau_{pi}^{j} = \tau_{oi}^{j} \geq 0$	0.0596	0.6686	0.0892	0.1917
(6)	$\kappa_{ip}^{j} = \infty \; \forall i,j$	0.0478	0.6217	0.0769	0.1738

Notes: This table contains results of counterfactual simulations as discussed in section 5.3. The first column indexes 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 $\left(p_n/p_{us} \equiv \Pi_{j=1}^{J}\left(p_n^j/p_{us}^j\right)^{\alpha^j}\right)$. 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 pays the same tariffs on imports as does ordinary. Row (3) allows processing producers 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 (e.g. $\lambda_p^j = \lambda_o^j$)but with imperfect correlation of draws. Row (5) is the same as row (3) except that processing producers pay the same tariffs on imports that ordinary producers do. Row (6) imposes infinite trade costs on all shipments out of the processing sector. $\theta^j = 4 \; \forall j$.

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.

We then ask what is the benefit from the duty free treatment that processing receives by asking what might happen to welfare if processing were subjected to the same tariffs as ordinary production.[43] Although Panagariya (1992) argues that the welfare effect of completely eliminating duty drawbacks from a positive level should be negative (pg. 144, proposition 5), our quantitative model is more complex than the setting in that paper and, therefore, the mapping of its welfare predictions to this exercise is unclear. Looking at row 2 of table 4, we find that real wages fall slightly although real income is nearly unchanged due to increased tariff revenue. However, these changes are quantitatively small. This reflects the fact that imports as a share of total demand in China is quite small (6% in the ordinary sector in 2000), and is consistent with the small effects of incremental trade liberalization found in Eaton and Kortum (2002) and Caliendo and Parro (2015). The last column shows that this loss in nominal wages is generally made up for by additional tariff revenue.

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 producers can sell to domestic consumers. 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 and processing producers share the same (perfectly correlated) productivity levels but consumers are allowed to buy from processing, the only welfare gain will come from the tariff free treatment of inputs which is small (see row 2). However, less than perfectly correlated productivity draws and different states of technology introduce the possibility of welfare gains due to comparative advantage. Our estimate of ν is important for this: if it is lower than out estimated value–as when we identify it in first differences–this will generate larger welfare

[43] More precisely, we set $\tau^j_{pi} = \tau^j_{oi}$ instead of setting $\tau^j_{pi} = 0$ as in the benchmark case (row 1).

gains from allowing Chinese consumers and producers to purchase processing output.[44]

We find major welfare effects. In the context of our model, a counterfactual world in which Chinese consumers can buy from processing producers displays real wages that are 14% higher (1.15 percentage points) and real income that is 10% higher (1.74 percentage points) than in the benchmark equilibrium. The reason that these effects is so large is that, *because of transportation costs*, 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 producers will have a much larger effect than a policy that affects the price charged on imports. The change in real income is less than the change in real wages because increased domestic sales by processing producers crowd out imports leading to lower tariff revenue.

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 producers 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 producers, $\nu = 0.71$. 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 considers a case in which the processing sector disappears and all Chinese production occurs under the ordinary regime. This is done by setting $\kappa_{ip}^j = \infty \; \forall i,j$

44 An assumption implicit in the framework upon which we draw is that production is irreversibly pre-committed to either ordinary or processing. For example, processing productivity is higher than for ordinary, agents cannot keep that processing draw, relinquish their duty rebates, obtain domestic market access, and sell through ordinary. Brandt and Morrow (2017) and Defever and Riano (2017) both discuss the many logistical hurdles that firms must navigate when choosing which organizational form in which to operate as well the additional hurdles that must be undertaken to switch from one organizational form to another. In carrying out our counterfactual analysis that processing firms can sell domestically, we are allowing goods that are produced through processing to be sold to the domestic market despite the fact that the organization of production is pre-committed to being through processing.

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 producers are nearly as large as the case in which processing producers 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 producers 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.[45]

5.31 The Welfare Effects of Processing: Robustness

We assess the robustness of our previous results by allowing for heterogeneity in θ^j as suggested by Caliendo and Parro (2015). We start by simulating the baseline model (table 4) imposing the values of θ^j estimated in Caliendo and Parro (2015).[46] The equilibrium in which Chinese consumers and producers can frictionlessly purchase from processing producers entails 14.3% higher real wages and 10% higher real income than the baseline equilibrium in which they cannot.[47] These alternate values of θ^j do not appear to affect our results.

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. Brandt and Morrow (2017) argue that falling levels of protection on intermediate inputs and capital equipment were a major contributor because this provided agents with a diminishing incentive to organize through processing and obtain duty free inputs. Manova and Yu (2016) argue that financial constraints were also important

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

[46] More precisely, for each four-digit ISIC code, we assign it the value of θ^j of the two-digit ISIC code to which it belongs as estimated by Caliendo and Parro (2015). We also reestimate ν which retains its value up to two decimal places.

[47] We do not find this surprising as the unweighted average for θ^j across our 109 three digit sectors is 5.20 which is close to our benchmark value of 4.

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

	2000	2001	2002	2003	2004	2005	2006	2007
$\frac{\sum_{j,i} X^j_{ip}}{\sum_{j,i} X^j_{ip}+X^j_{io}}$	0.609	0.604	0.601	0.609	0.609	0.591	0.565	0.506

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.

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. 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.[48] 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 share had fallen a little more than 20% (12.9 percentage points) to 47.5%.[49]

Table 6 presents our counterfactual simulations. In each row, the second column describes the set of tariffs used for the counterfactual. For example, if $\widehat{\tau}^j_{oi,2007} = \tau^j_{oi,2007}$, Chinese tariffs to their 2007 level and, if $\widehat{\tau}^j_{oi,2007} = \tau^j_{oi,2000}$, tariffs are 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.

[48]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.

[49]This change is larger than that documented in Brandt and Morrow (2017). This is because data requirements in this paper force us to focus on larger countries with which China trades. Processing is generally more prominent in trade with those countries and has also fallen by more between 2000 and 2007.

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	$\tau^j_{oi,2000}$	$\lambda^j_{o,2000}$	$\lambda^j_{p,2000}$	0.593
2	$\tau^j_{oi,2007}$	$\lambda^j_{o,2000}$	$\lambda^j_{p,2000}$	0.566
3	$\tau^j_{oi,2000}$	$\lambda^j_{o,2007}$	$\lambda^j_{p,2007}$	0.527
4	$\tau^j_{oi,2007}$	$\lambda^j_{o,2007}$	$\lambda^j_{p,2007}$	0.507

Notes: This table presents our 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.

Row 1 holds tariffs and productivity constant at their 2000 level. The predicted aggregate share of exports organized through ordinary trade (0.593) is very close to the actual number (0.609). Row 2 feeds in actual changes in tariffs in China holding all productivity terms constant.[50] 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 31% of the total change in ordinary exports (2.7 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 77% (6.6 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 all of the change.

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 33% of the

[50]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.

total change. Similarly, increasing productivity in ordinary production relative to processing, and increasing productivity overall explain approximately 77% of the total change. Combined these two effects are consistent with the entirety 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 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 producers 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 agents engaging in processing are not simply replicating ordinary production. 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 producers 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 producers 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

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

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

$$G^j_{ni}(p) = 1 - \exp\left[\lambda^j_i \left(c^j_i \kappa^j_{ni}\right)^{-\theta^j} p^{-\theta^j}\right]. \tag{A1}$$

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

$$G^j_{nc}(p) = 1 - \exp\left[\left(\left(\lambda^j_o\right)^{\frac{1}{1-\nu}} \left(c^j_o \kappa^j_{no}\right)^{-\frac{\theta^j}{1-\nu}} + \left(\lambda^j_p\right)^{\frac{1}{1-\nu}} \left(c^j_p \kappa^j_{np}\right)^{-\frac{\theta^j}{1-\nu}}\right)^{1-\nu} p^{\theta^j}\right]. \tag{A2}$$

A.1 Non-China Destinations

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

$$G^j_n = 1 - \left\{\left[\prod_{i=1}^{N}(1 - G^j_{ni}(p))\right]\left[1 - G^j_{nc}(p)\right]\right\}. \tag{A3}$$

Using equations (A1), (A2), and (A3), the distribution of prices in any non-Chinese destination market is given by

$$G^j_n = 1 - \exp\{-\Phi^j_n p^{\theta^j}\} \tag{A4}$$

where

$$\Phi^j_n \equiv \left[\left(\lambda^j_o\right)^{\frac{1}{1-\nu}} \left(c^j_o \kappa^j_{no}\right)^{-\frac{\theta^j}{1-\nu}} + \left(\lambda^j_p\right)^{\frac{1}{1-\nu}} \left(c^j_p \kappa^j_{np}\right)^{-\frac{\theta^j}{1-\nu}}\right]^{1-\nu} + \left[\sum_{i=1}^{N} \lambda^j_i \left(c^j_i \kappa^j_{ni}\right)^{-\theta^j}\right] \tag{A5}$$

A.2 Ordinary Importing in China

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

$$G^j_o = 1 - \left\{\left[\prod_{i=1}^{N}(1 - G^j_{oi}(p))\right]\left[1 - G^j_{oo}(p)\right]\right\}.$$

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

$$G^j_o = 1 - \exp\{-\Phi^j_o p^{\theta^j}\}$$

where

$$\Phi_o^j \equiv \lambda_o^j \left(c_o^j \kappa_{on}^j\right)^{-\theta^j} + \sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{oi}^j\right)^{-\theta^j}.$$

A.3 Processing Importing in China

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

$$G_p^j = 1 - \left\{ \left[\prod_{i=1}^{N} (1 - G_{pi}^j(p))\right] \left[1 - G_{po}^j(p)\right] \right\}$$

The processing sector cannot purchase from processing product lines in China. 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

$$\Phi_p^j \equiv \lambda_o^j \left(c_o^j \kappa_{pn}^j\right)^{-\theta^j} + \sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{pi}^j\right)^{-\theta^j}.$$

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 (A4) and (A5), this is equivalent to

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

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

Because ordinary agents cannot purchase processing output, in ordinary sector, the share of expenditure on goods accruing to country i can be derived using the expression above and $\kappa_{op}^j = \infty$:

$$\pi_{oi}^j = \frac{\lambda_i^j (c_i^j \kappa_{oi}^j)^{-\theta^j}}{\lambda_o^j \left(c_o^j \kappa_{oo}^j\right)^{-\theta^j} + \sum_{i'=1}^N \lambda_{i'}^j \left(c_{i'}^j \kappa_{oi'}^j\right)^{-\theta^j}}.$$

Similarly, with $\kappa_{pp}^j = \infty$, the expenditure share of processing sector is given by:

$$\pi_{pi}^j = \frac{\lambda_i^j (c_i^j \kappa_{pi}^j)^{-\theta^j}}{\lambda_o^j \left(c_o^j \kappa_{po}^j\right)^{-\theta^j} + \sum_{i'=1}^N \lambda_{i'}^j \left(c_{i'}^j \kappa_{pi'}^j\right)^{-\theta^j}}.$$

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.

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

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

$$G_n^j(w_n^j) = 1 - \exp\left[-\underbrace{(c_o^j \kappa_{no}^j)^{\theta^j} \sum_{i \neq o,p} \lambda_i^j (c_i^j \kappa_{ni}^j)^{-\theta^j}}_{\lambda_{w_n}^j} {w_n^j}^{-\theta^j} \right] \tag{A6}$$

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

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

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.

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

where

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

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

Adding last two expressions delivers

$$\frac{{\lambda_o^j}^{\frac{1}{1-\nu}} {\mu_n^j}^{-\frac{\theta^j}{1-\nu}}}{{\lambda_o^j}^{\frac{1}{1-\nu}} {\mu_n^j}^{-\frac{\theta^j}{1-\nu}} + {\lambda_p^j}^{\frac{1}{1-\nu}}} \left\{ 1 - exp[-\left({\lambda_o^j}^{\frac{1}{1-\nu}} + {\lambda_p^j}^{\frac{1}{1-\nu}} {\mu_n^j}^{-\frac{\theta^j}{1-\nu}} \right)^{1-\nu} (w_n^j)^{-\theta^j}] \right\} \tag{A7}$$

Integrating equations (A7) over w_n, we get

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

where the second equality follows from the distribution function (A6). Substitute in $\mu_n^j=\frac{c_o^j\kappa^j_{no}}{c_p^j\kappa^j_{np}}$ and $\lambda^j_{wn}=(c^j_o\kappa^j_{no})^{\theta^j}\sum_{i\neq o,p}\lambda^j_i(c^j_i\kappa^j_{ni})^{-\theta^j}$ into the last equality, π^j_{no} can be rewritten as

$$\pi^j_{no}=\frac{\lambda_o^{j\,\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}(c^j_p\kappa^j_{np})^{-\frac{\theta^j}{1-\nu}}}\frac{[\lambda_o^{j\,\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}(c^j_p\kappa^j_{np})^{-\frac{\theta^j}{1-\nu}}]^{1-\nu}}{[\lambda_o^{j\,\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}(c^j_p\kappa^j_{np})^{-\frac{\theta^j}{1-\nu}}]^{1-\nu}+\sum_{i\neq o,p}\lambda^j_i(c^j_i\kappa^j_{ni})^{-\theta^j}}$$

Note that the term $\frac{\lambda_o^{j\,\frac{1}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}\mu_n^{j\,-\frac{\theta^j}{1-\nu}}}$ captures the relative size of ordinary trade in market n. It is higher when the fundamental productivity of ordinary trade λ^j_o is relative higher, or relative cost of ordinary trade μ^j_n is lower. The second term $\frac{[\lambda_o^{j\,\frac{1}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}\mu_n^{j\,-\frac{\theta^j}{1-\nu}}]^{1-\nu}}{[\lambda_o^{j\,\frac{1}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}\mu_n^{j\,-\frac{\theta^j}{1-\nu}}]^{1-\nu}+\lambda^j_{w_n}}$ 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

$$\pi^j_{np}=\frac{\lambda_p^{j\,\frac{1}{1-\nu}}\mu_n^{j\,-\frac{\theta_j}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}\mu_n^{j\,-\frac{\theta_j}{1-\nu}}}\frac{[\lambda_o^{j\,\frac{1}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}\mu_n^{j\,-\frac{\theta_j}{1-\nu}}]^{1-\nu}}{[\lambda_o^{j\,\frac{1}{1-\nu}}+\lambda_p^{j\,\frac{1}{1-\nu}}\mu_n^{j\,-\frac{\theta_j}{1-\nu}}]^{1-\nu}+\lambda^j_{w_n}} \tag{A8}$$

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.[51]

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

[51]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.[52] 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

$$\frac{X^j_{po}}{X^j_{oo}} = \frac{X^j_p / \Phi^j_p}{X^j_o / \Phi^j_o} \tag{A9}$$

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

$$\frac{X^j_{pW}}{X^j_{oW}} = \frac{\sum_{i=1}^{N} \lambda^j_i \left(c^j_i \kappa^j_{pi}\right)^{-\theta^j}}{\sum_{i=1}^{N} \lambda^j_i \left(c^j_i \kappa^j_{oi}\right)^{-\theta^j}} \frac{X^j_p / \Phi^j_p}{X^j_o / \Phi^j_o} \tag{A10}$$

[52]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

$$\frac{X^j_{pW}}{X^j_{oW}} = \left[\frac{\sum_{i=1}^N (1+\tau^j_{ci})^{\theta^j} X^j_{oi}}{\sum_{i=1}^N X^j_{oi}}\right] \frac{X^j_p/\Phi^j_p}{X^j_o/\Phi^j_o}. \tag{A11}$$

Combining equations (A12) and (A11), we can obtain

$$\frac{X^j_{po}}{X^j_{oo}} = \frac{X^j_{pW}}{X^j_{oW}} \left[\frac{\sum_{i=1}^N (1+\tau^j_{ci})^{\theta^j} X^j_{oi}}{\sum_{i=1}^N X^j_{oi}}\right]^{-1} \tag{A12}$$

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. Price Index and Relative Productivity of Nontraded Sector

To compute the price index of nontraded sector, we collect 1996 and 2011 data from the International Comparison of Prices Program (ICP). The price index of nontraded goods is constructed as the expenditure weighted average of prices in the following sectors: Health, Transport, Communication, Recreation and culture, Education, Restaurants and hotels, and Construction. Using data of PPP-adjusted per capita GDP from the Penn World Tables, we impute the price index for 2000 and 2007 by estimating the following model:

$$\ln p^{J+1}_{nt} = \beta_0 + \beta_1 \ln GDP_{nt} + \beta_2 \ln GDP^2_{nt} + \beta_3 \ln GDP^3_{nt} + \beta_4 \ln GDP^4_{nt} + \beta_5 \mathbf{1}(t=2011) + \varepsilon_{nt}.$$

In particu lar, the price index of nontraded goods in 2000 is computed as

$$p^{J+1}_{n,00} = \exp[\hat\beta_0 + \hat\beta_1 \ln GDP_{n,00} + \hat\beta_2 \ln GDP^2_{n,00} + \hat\beta_3 \ln GDP^3_{n,00} + \hat\beta_4 \ln GDP^4_{n,00} + \frac{4}{15}\hat\beta_5].$$

Similarly, the price index for 2007 is computed as

$$p^{J+1}_{n,07} = \exp[\hat\beta_0 + \hat\beta_1 \ln GDP_{n,07} + \hat\beta_2 \ln GDP^2_{n,07} + \hat\beta_3 \ln GDP^3_{n,07} + \hat\beta_4 \ln GDP^4_{n,07} + \frac{11}{15}\hat\beta_5].$$

Based on the imputed price indices, the relative productivity of non-traded sector is constructed from (the time index is suppressed):

$$\frac{\lambda^{J+1}_n}{\lambda^{J+1}_{us}} = \left[\left(\frac{w_n}{w_{us}}\right)^{\tilde\gamma^{J+1}_{0,n}} \left(\frac{r_n}{r_{us}}\right)^{\tilde\gamma^{J+1}_{1,n}} \Pi^{J+1}_{k=1}\left[\frac{p^k_n}{p^k_{us}}\right]^{\tilde\gamma^{k,J+1}}\right]^{\theta^{J+1}} \left[\frac{p^{J+1}_n}{p^{J+1}_{us}}\right]^{-\theta^{J+1}}$$

Appendix E. Solution Algorithm

To simply the illustration, we introduce the new notation $\kappa_{ni}^j = t_i^j \tilde{\kappa}_{ni}^j$. By definition $\tilde{\kappa}_{ni}^j = (1+\tau_{ni}^j)(d_{ni}^j)^{\beta_j}$. With parameters θ_j, ν, $\gamma_{0,n}^j$, $\gamma_{1,n}^j$, γ_n^{jk}, α^j, L_n and K_n, and estimates of $\tilde{\lambda}_n^j \equiv \frac{\lambda_i^j}{\lambda_{us}^j}$, $\tilde{\kappa}_{ni}$, $\frac{t_i^j}{t_{us}^j}$ $(i=1,...,N)$ and $(\lambda_{us})^{-\frac{\nu}{\theta_j}} \frac{t_c^j}{t_{us}^j}$, we can solve the model using the following solution algorithm:

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

- Solve relative prices $\frac{P_n^j}{P_{us}^j}$ and variable production costs $\tilde{c}_n^j \equiv \frac{c_n^j}{c_{us}^j}$ from the following equations:

$$\tilde{c}_n^j \equiv \frac{\Upsilon_n^j}{\Upsilon_{us}^j} \left(\frac{w_n}{w_{us}}\right)^{\tilde{\gamma}_{0,n}^j} \left(\frac{r_n}{r_{us}}\right)^{\tilde{\gamma}_{1,n}^j} \Pi_{k=1}^{J+1} \left[\frac{p_n^k}{p_{us}^k}\right]^{\gamma^{kj}} \qquad \text{for all } n=1,...,N,o \text{ and } j$$

For $j=1,...,J$,

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

For $j=J+1$,

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

- 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}+\Sigma_{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}+\Sigma_{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}+\Sigma_{i'=1}^N\tilde{\lambda}_{i'}^j\left(\tilde{c}_{i'}^j\kappa_{ni'}^j\right)^{-\theta^j}} \end{cases}$$

  For $n = o$,

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

  For $n = p$,

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

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

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

  For $n = o$,q

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

  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:

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

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