Is Processing Good?: Theory and Evidence from China *

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ABSTRACT:

Policies promoting processing trade are thought to encourage integration into global markets for developing countries. Agents engaged in processing can import intermediate inputs and capital equipment duty-free but often cannot sell these inputs or resulting output on their own domestic market. We study these policies' welfare effects using Chinese data for 109 industries for 2000-2007. Counterfactual experiments imply welfare losses of 3-7% for Chinese agents due to the restriction on selling processing output domestically. Processing's duty-free status entails smaller welfare gains (<1%). We also develop a new method for estimating correlation parameters for multivariate Fréchet distributions in multiplicative gravity models.

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1. Introduction

Trade economists and development practitioners have long believed that policies encouraging integration into the global economy help expedite economic development [e.g. Frankel and Romer (1999) and Redding and Venables (2004)]. One common lever toward this end is the establishment of export processing zones and the adoption of policies that encourage firms to engage in export processing. Radelet and Sachs (1997) argue that such programs have been instrumental in the successful economic development of East and Southeast Asia.

A central feature of processing regimes is that firms do not have to pay tariffs on the import of intermediate goods and capital equipment as long as they are used exclusively in the production of goods for export. However, these same firms are often restricted from selling output using these imported inputs on the domestic market.[1] Processing trade typically co-exists with "ordinary trade" under which firms are required to pay tariffs on imports but are then free to sell the resulting output (or the imported good itself) on the domestic market.

In an environment of high tariffs, processing trade allows low-income countries to better leverage their low labor costs in labor-intensive manufacturing assembly, leading to an increase in labor demand and foreign exchange earnings. At the same time however, processing introduces a new distortion into the local economy: local agents are not able to consume the goods produced by export processors. Insofar as there are differences between processing and ordinary producers in the varieties they produce, the technology they use, or their productivity, there are potential welfare costs from such policies. Ex ante, there are number of potential reasons why productivity might differ between the two organizational forms, largely related to differences in the tasks carried out and the capabilities required (e.g. quality assurance, logistics and supply chain management, and design) and the prominence of foreign firms in the two organizational forms.[2]

[1]These restrictions have been a prominent feature of two of the most well-known cases of export processing. In China, processing output cannot be sold domestically. In Mexico, initial restrictions on maquiladoras from selling domestically were gradually relaxed under NAFTA. From a complete prohibition before NAFTA, in 1993, firms were allowed to sell 50% of the previous year's export production on the domestic market, and, in 2001, 70-90%. See Vargas (2001) and Canas and Gilmer (2007).

[2]We discuss possible reasons for these differences in detail in section 6.

Despite the prevalence of these programs, there are relatively few quantitative cost-benefit analyses.[3] This paper carries out such an analysis by examining the welfare implications of China's processing regime for the years 2000-2007. We extend the multi-sector, multi-country, general equilibrium models of the sort developed by Eaton and Kortum (2002), Caliendo and Parro (2015), and Levchenko and Zhang (2016), to include both the ordinary and processing trade. We allow for multiple factors of production (capital and labor) as well as traded intermediate inputs, which are essential for thinking about the implications of China's trade regime.

Our analysis has two major components. First, we examine productivity differences between ordinary and processing production, a likely determinant of the costs of restrictions on the processing sector. We obtain estimates of relative productivity for ordinary and processing using estimates of its dual relative unit costs from gravity regressions. Second, through a series of counterfactual experiments, we assess the welfare consequences of processing. The first experiment examines the welfare gains of the tariff exemption enjoyed by processing firms. The second experiment assesses the potential welfare costs stemming from the restrictions on the sale of processing output in the domestic economy.

In our examination of productivity, we allow for differences between ordinary and processing both within and across industries. Using the multivariate Fréchet distribution as in Ramondo and Rodríguez-Clare (2013), we assume productivity draws for ordinary and processing within an industry are stochastic but imperfectly correlated. This captures our prior that productivity draws in ordinary and processing production are unlikely the same, but might still be correlated. To estimate the degree of correlation, we introduce a new method that combines the insights of Berry (1994) and Caliendo and Parro (2015).[4] Our estimated value for this correlation suggests that

[3]Panagariya (1992) offers an early welfare analysis of duty drawbacks in the context of a small open economy, which Ianchovichina (2007) builds on to assess the welfare effects of tariff drawbacks for China. Connolly and Yi (2015) offers an assessment of duty drawbacks for Korea in a full general equilibrium model. However, both Ianchovichina (2007) and Connolly and Yi (2015) assume that all exports receive drawbacks and therefore do not explore the endogenous choice of how to organize between ordinary or processing production. In addition, neither paper explores the potential welfare losses when processing firms cannot selling domestically. Madani (1999) and OECD (2007) offer descriptive analysis of processing but do not engage in formal cost-benefit analysis.

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

the idiosyncratic portions of the productivity draws for ordinary and processing production are correlated.[5] However this correlation is far from perfect which implies room for both within- and across-industry comparative advantage gains through allowing processing to sell domestically.

Several major findings emerge from our analysis. First, although total factor productivity (TFP) for processing Chinese production is slightly lower on average than ordinary, there are significant differences across industries. In 2000, for example, the TFP premium of processing relative to ordinary production ranges from -32% to +25%. This heterogeneity suggests that looking at a single premium estimated over all industries may be misleading, and that there are potentially large comparative-advantage gains from allowing processing to sell domestically.[6]

Second, we find relatively small welfare gains from the duty drawbacks enjoyed by the processing sector. This is consistent with small estimated welfare effects of incremental international trade liberalization in quantitative trade models such as Eaton and Kortum (2002) and Caliendo and Parro (2015), and the fact that processing represents less than 5% of aggregate gross output in China in 2000.[7]

Third, we find large welfare *gains* in the domestic economy from eliminating the restriction on domestic sales for the processing sector. We estimate that the real wages in China in 2000 would have been approximately 7% higher in a world with no restrictions. The increase in real income would have been smaller ($\approx$ 3%) due to smaller gains for owners of capital and a loss of tariff income as increased processing sales crowd out imports.[8] Laborers are better off relative to

[5] 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. For this reason, we assume perfect competition and constant returns to scale in output markets such that firms have no role in our model. This makes the organization of production at the goods level our object of interest, and not the organization of the firm. Liu and Ma (2018) offer a general equilibrium model of margins of trade in China building on Melitz (2003). They assume that every firm takes both an ordinary and a processing draw and chooses a single organizational form at the firm level.

[6] Because we are explicitly interested in productivity differences between ordinary and processing production, and their potential effect on welfare, we solve the model in levels as in Levchenko and Zhang (2016), and not in differences as in Caliendo and Parro (2015) (i.e. "hat algebra").

[7] Processing represents approximately 10% of manufacturing sales in our data. Manufacturing, on the other hand, is approximately 45% of gross aggregate output [Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)].

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

owners of capital for two reasons: first, processing is generally more labor intensive than ordinary production; and second, the processing sector grows from 13% to 45% of tradable output in the counterfactual.

Large documented barriers to international trade likely underlie our finding of larger gains from eliminating the restriction on domestic sales for processing than international trade liberalization. Because domestic sales face substantially lower barriers than imports, endogenous domestic expenditure shares for domestically produced goods are higher. As a result, falling prices for domestically produced goods will have relatively larger effects on the overall price index.[9] 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), Ramondo, Rodríguez-Clare and Saborío-Rodríguez (2016), and Tombe and Zhu (forthcoming)].

This paper is linked to an emerging literature that examines the role of distortions in the development of the Chinese economy. Hsieh and Klenow (2009) and Song, Storesletten and Zilibotti (2011), for example, examine the role of state-introduced distortions in capital market. Brandt, Adamopoulos, Leight and Restuccia (2017b) examine the effect of distortions in the market for farmland. Our study of the welfare effects of China's processing regime is also related to Defever and Riano (2017) who find welfare losses resulting from export subsidies. Branstetter and Lardy (2008) argue that China's processing regime helped to reduce the distorting effect of tariffs however they do not consider the costs of the restrictions on domestic sales.[10]

Section 2 reviews institutional details related to China's processing regime. Section 3 describes the model that we bring to our question. Section 4 describes the data. Section 5 details how we map the model to the data. Section 6 presents our results including estimates of relative

[9]Variable mark-ups introduce the possibility of lower prices by domestic producers due to increased import competition. However, as shown in Arkolakis, Costinot, Donaldson and Rodríguez-Clare (2018a), foreign producers may increase their mark-ups on exports to China in response, thereby offsetting some of the gains from lower domestic mark-ups. Defever and Riano (2017) explore the welfare effects 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 discouraged entry by Chinese firms into China's domestic markets, leading to a higher domestic price index.

[10]Because many processing firms are also foreign multinationals, policies that impede their expansion, such as the prohibition on domestic sales, might also affect the take-up of new technologies in China or diffusion to local suppliers. Measuring the strength of these effects is empirically difficult however and left as a source for future research.

productivity between ordinary and processing and the results of the counterfactual simulations. Section 7 concludes.

2. Context/Institutions

We briefly review select institutional details of China's processing regime that are pertinent to this paper.[11] China's processing regime was established in 1979 and provided incentives for the processing of raw materials, parts, and components used for exports [Branstetter and Lardy (2008)]. Throughout this period, the goal of the trade regime was to generate foreign exchange while maintaining the protection of domestic industry through tariffs on imports. Because 100% of processing output was exported, and none could be sold domestically, both goals were easily achieved.[12]

In the aggregate, the export share of processing increased between 1990 and 2000 and then began to fall. In 2000, processing exports represented 55.2% of China's total exports, but by 2006 this fell to 52.6% and in 2012 were only 39.1%.[13] Increasing domestic capabilities, which made it easier for firms to source locally higher quality inputs, and a growing domestic market likely contributed to this decline, as did falling tariff levels, which reduced the incentive to organize through processing. In China, tariffs began to come down in the early 1990s as part of a comprehensive set of external reforms culminating in WTO accession. Between 2000 and 2007, tariffs (unweighted) fell even further from 17.3% in 2000 to 9.1% in 2007.

[11] 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". For much more detailed discussions of these trade forms, see discussions in Feenstra and Hanson (2005), Branstetter and Lardy (2008), Fernandes and Tang (2012).

[12] The location of the first special economic zones in Guangdong and Fujian put them near Hong Kong and Taiwan, the sources of much of the FDI into the sector, and helped to assuage concerns over any effect on established industry centers, including those in Beijing and Shanghai.

[13] In the data used in this paper, the decline is larger: from 61% of total exports in 2000 to 51% in 2007. This reflects the fact that processing exports are more prominent in trade with industrialized countries that dominate the sample we use. We discuss the sample in detail in section 4 including criteria to be included.

The size of the welfare gains from allowing processing firms to sell domestically partially depends on the productivity differences between the two organizational forms. If there are no differences, then there are no gains from allowing processing to sell domestically (aside from tariff treatment differences). A small but developed literature has found that Chinese processing firms are, on average, less productive than ordinary and also experienced slightly slower productivity growth than ordinary between 2000 and 2006.[14] Taken at face value, these findings suggest minimal gains. However, this literature usually ignores differences across industries which can be a source of gains when processing has a comparative advantage in some goods and industries. In addition, productivity differences across varieties within an industry can generate *within-industry* gains from comparative advantage.[15] We discuss these differences in detail in section 6.2.

3. Model

Our quantitative model possesses several important features. First, all prices and quantities are endogenous equilibrium outcomes. Second, rich input-output linkages capture the reliance of processing on imported intermediate inputs. Third, the presence of multiple industries allows us to capture the empirical fact that processing tends to be more prominent in certain industries [e.g. Brandt and Morrow (2017)], and that there are differences in the productivity of processing relative to ordinary across industries. Finally, we allow for multiple factors of production in order to help distinguish productivity from differences in capital intensity.

We model ordinary and processing trade to reflect their policy treatment: processing production does not face tariffs on imports of intermediate inputs but cannot be sold on domestic (i.e. Chinese) markets. Ordinary production faces import tariffs but faces no restriction from selling on domestic markets. Consequently, ordinary output can be used in processing production but the reverse is not allowed. In the rest of the paper, we refer to sales or exports through ordinary and processing as

[14]See Yu (2015), Table 9. Also see Manova and Yu (2016) and Dai, Maitra and Yu (2016).

[15]This heterogeneity is measured by the parameter θ in models based on Eaton and Kortum (2002) and is closely related to the elasticity of substitution in models based on Krugman (1980) which governs the strength of love of variety.

the "organization of production" or the "organization of trade", respectively. We further assume that this distinction holds only for China: all other countries engage only in ordinary trade exclusively.[16]

3.1 Preliminaries

In addition to China, there are N countries indexed by n,i. Because our model is static, we suppress the time subscript for now. 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). Notationally, there are $N+2$ "countries", with countries other than China indexed by $n = 1$,...,N, and the $N+1^{th}$ and the $N+2^{nd}$ terms representing ordinary and processing production in China, respectively. In some cases, we use the subscript c for China, for example, when we reference the utility function of its representative consumer or factor prices that are common across the two organizational forms.

Each country possesses exogenous endowments of the primary factors 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. In China, labor and capital are fully mobile across ordinary and processing, with factor returns w_c and r_c.[17]

Within each 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.

[16]Firms engaged in processing sometimes also receive tax breaks and/or subsidized land. Since these policies are targeted more generally at multinationals to attract FDI and are not processing-specific, we only focus on tariff treatment and domestic market access in this paper when distinguishing between ordinary and processing trade.

[17]We treat traded machinery and equipment as an intermediate good whose price differs for ordinary and processing production due to differential tariff treatment and because processing imports cannot be sold domestically, which prevents price arbitrage. For this reason, capital K_n is best thought of as comprising the non-traded component of the capital stock.

3.2 *Demand*

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

3.3 *Production*

Production of any variety ω^j requires labor, capital, and intermediate inputs. Producers differ in their efficiency of production $z_n^j(\omega^j)$. 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 $\gamma_{l,n}^j + \gamma_{k,n}^j + \sum_{k=1}^{J+1}\gamma_n^{kj} = 1$. $l_n^j(\omega^j)$ 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 required. The factor cost shares vary across both industries and countries. Unit cost is $c_n^j/z_n^j(\omega^j)$ where the cost of an input bundle is

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

and Υ_n^j is an industry-country specific constant.[18] p_n^k is the price of a composite unit of k in country n.

As in Caliendo and Parro (2015), the composite intermediate in sector j, Q_n^j, is a CES aggregate of industry-specific varieties given by $Q_n^j = \left[\int x_n^j(\omega^j)^{\frac{\sigma^j-1}{\sigma^j}}d\omega^j\right]^{\frac{\sigma^j}{\sigma^j-1}}$ where $x_n^j(\omega^j)$ is the demand for intermediate goods ω^j from the lowest cost supplier. Because this composite is used either for intermediate inputs for downstream production or final goods consumption, market clearing implies $Q_n^j = C_n^j + \sum_{k=1}^{J+1}\int m_n^{jk}(\omega^k)d\omega^k$. This expression holds for ordinary production as well. For processing, $Q_p^j = \sum_{k=1}^{J}\int m_p^{jk}(\omega^k)d\omega^k$ since all of the composite processing output must be used in the production of processing goods and cannot be used to satisfy final demand.[19]

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

[19] Our model imposes the assumption that the entire non-traded sector is organized through ordinary production.

3.4 *Transport Costs and Pricing*

As in Eaton and Kortum (2002), a given variety is only produced in a country in equilibrium if that country is the lowest cost provider of the variety in some market. Trade costs 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 destinations.

There are two components of trade costs: ad-valorem tariffs and iceberg international trade costs. The statutory ad-valorem tariff that n imposes on varieties of good j shipped from i is given by τ_{ni}^j. All exports from China are subject to the same tariff level regardless of their organization such that $\tau_{ic}^j = \tau_{io}^j = \tau_{ip}^j$. We model the iceberg costs as a weakly increasing industry-specific function of distance, $g^j(d_{ni})$, where d_{ni} is the distance between n and i. We assume $g^j(d_{ni})$ is symmetric in distance with $g^j(d_{ni}) = g^j(d_{in})$. To allow for asymmetries, we follow Waugh (2010), and introduce an exporter i-industry j specific multiplicative iceberg costs t_i^j to allow total iceberg costs between two locations to depend on the direction of shipment. Combined, the total trade 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.

3.5 *Productivity Distributions*

Ricardian motives for trade follow Eaton and Kortum (2002). Outside of China, those in country i-industry j draw from Fréchet 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 $\left(\lambda_i^j\right)^{\frac{1}{\theta^j}}$. The parameter θ^j captures heterogeneity across varieties in countries' relative efficiencies, and governs comparative advantage within an industry.

For ordinary and processing trade within a Chinese industry, draws between the two organizational forms are not likely to be independent nor taken from a distribution with a single state of technology. Thus, 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 Fréchet distribution which varies by industry:

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

where λ_o^j and λ_p^j reflect states of technology in the two organizational forms, and $\nu \in [0,1)$ governs the correlation between z_o and z_p. Analogous to the role of θ^j, ν regulates heterogeneity in relative efficiency between ordinary and processing across varieties. It therefore governs *within-industry* comparative advantage across the two organizational forms. As the correlation increases ($\nu \to 1$), the draws are more correlated, there is less heterogeneity, and there are smaller gains from being able to buy from both forms of production. As the correlation declines ($\nu \to 0$), the opposite holds true. $\nu = 0$ corresponds to the case where z_o and z_p are independent.

3.6 Equilibrium Trade Shares

We now define equilibrium expenditure shares for each country. Outside of China, the share of total expenditures by (importing) country n in industry j on exports from (exporter) i, or π_{ni}^j, is given by:

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

where

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

For China, the expenditure shares for ordinary and processing need to be modified. The share of expenditure on sector j goods in destination n on ordinary production in China is given by:

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

The first term to the right of the equality in equation (6) is the share of ordinary exports in total *Chinese* exports to destination market n. The second term is the share of country n expenditures going to China as a whole. The share of ordinary is increasing in its relative productivity, λ_o^j/λ_p^j, but decreasing in its relative costs, c_o^j/c_p^j, and iceberg trade $\kappa_{no}^j/\kappa_{np}^j$.[20] Similarly, the expenditure share for 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 for the processing and ordinary sectors in China is straightforward 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.[21] This allows us to derive a share of expenditure by processing on country i as $\pi_{pi}^j = \frac{\lambda_i^j(c_i^j\kappa_{pi}^j)^{-\theta^j}}{\Phi_p^j}$, where Φ_p^j is obtained by setting $n = p$ and $\kappa_{pp} = \infty$ in equation (5). The share of expenditures in destination o on goods from source i is given analogously: $\pi_{oi}^j = \frac{\lambda_i^j(c_i^j\kappa_{oi}^j)^{-\theta^j}}{\Phi_o^j}$, where Φ_o^j is given by setting $n = o$ and $\kappa_{op}^j = \infty$ in equation (5). Appendix A provides proofs of all expenditure shares.[22] Finally, as in Eaton and Kortum (2002), price distributions are give by:

$$p_n^j = A^j\left[\Phi_n^j\right]^{-\frac{1}{\theta^j}} \tag{8}$$

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.

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

[21]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 5. Empirically, we find that exporting firms that engage in processing alone 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%.

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

3.7 *Goods Market Clearing*

Total expenditure on industry j for country n can be decomposed as:

$$X_n^j = \alpha^j I_n + \sum_{k=1}^{J+1} \gamma_n^{jk} \left[\sum_{i=1}^{N+2} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k} \right]. \tag{9}$$

The first component ($\alpha^j I_n$) reflects final consumption expenditure on the industry j composite good in n. For a given (downstream) industry k-country i pair, the second component, $\gamma_n^{jk} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k}$, 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 over i gives global industry k expenditure to industry j-country n intermediate inputs; 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:

$$X_o^j = \alpha^j I_c + \sum_{k=1}^{J+1} \gamma_o^{jk} \left[\sum_{i=1}^{N+2} X_i^k \frac{\pi_{io}^k}{1+\tau_{io}^k} \right]. \tag{10}$$

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

$$X_p^j = \sum_{k=1}^{J} \gamma_p^{jk} \sum_{i=1}^{N} X_i^k \frac{\pi_{ip}^k}{1+\tau_{ip}^k}. \tag{11}$$

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 $M_{ni}^j = X_n^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j}$.

3.8 *Balanced Trade and Factor Market Clearing*

We impose the assumption that income equals expenditure, which implies that a country's income equals its total global expenditures. A similar expression also holds for China based on ordinary and processing trade. In addition, total payments to labor in a given country are equal to total world expenditures on output in a given country-industry pair times labor's share, summed across industries. A similar condition holds for capital. For more details, see Appendix A.

3.9 *Equilibrium*

Definition 1 *Given* L_n, K_n, λ_n^j, $g^j\,(d_{ni})$, t_n^j, α_n^j, γ_n^{jk}, $\gamma_{l,n}^j$, $\gamma_{k,n}^j$, ν, σ^j, *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)-(11), *balanced trade, and factor market clearing for all* j,n.

4. Data

The Data Appendix describes our data in detail, and here we briefly discuss key aspects of it. Based on country availability, our data cover 109 manufacturing sectors, and one non-traded sector for 24 developed and developing countries for the years 2000-2007. Manufacturing industries are at the four-digit ISIC level, with the non-traded sector a composite of services and agriculture. For countries other than China, trade data come from the BACI data base maintained by CEPII.[23] For Chinese exports and imports, transactions data from the Customs Administration of China allow us to distinguish ordinary and processing shipments. To calculate domestic sales by domestic producers at the country-industry level, we use output data from the UN IDSB data base and subtract exports from the same source to obtain domestic shipments. For China, these data come from the Annual Survey of Manufacturers carried out by the National Bureau of Statistics.[24] We subtract exports from the Customs Administration to obtain domestic sales.[25] All remaining data used in estimation of the gravity model come from CEPII (distance and contiguity measures) or UN TRAINS (tariff data). In terms of aggregate variables, total employment, cost of capital, and the

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

[24]Unlike INDSTAT, the IDSB contains both export and production data from one source which makes it ideal for calculating domestic shipments. However, it does not contain input data necessitating the need for INDSTAT discussed below. The IDSB data set does not contain data for China, thus our use of the NBS production data.

[25]These data do not distinguish whether sales by Chinese firms are to ordinary or to processing firms (processing firms do not sell domestically but can source 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. In addition, since the NBS data only cover firms with sales larger than 5 million (RMB) and the trade data are the universe of transactions, we scale up the NBS data by the ratio of manufacturing output in the 2004 census to output in the 2004 NBS annual firm survey for each industry.

(real) capital stock both come from the Penn World Tables 9.0. INDSTAT provides data for national wages.[26]

The cost share of labor $\gamma^j_{l,n}$ is the ratio of wages to total output 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 from the same sources. We assume that capital's share of output, $\gamma^j_{k,n}$, is one minus labor's share and the share of intermediate inputs. For China, these statistics are derived from the Annual Survey of Manufacturers.[27] We calculate γ^{jk}_n by starting with the world input-output matrix as published by Timmer et al. (2015). At the NACE level, this provides the shares of intermediate inputs of each input industry. We denote these as $\tilde{\gamma}^{j'k'}$ where $'$ denotes a NACE sector. Using a concordance available from WITS and a proportionality assumption, we calculate ISIC-specific intermediate input shares, $\tilde{\gamma}^{jk}$. Multiplying these by one minus the value added share, we obtain γ^{jk}_n.

5. Mapping Theory onto Empirics

5.1 *Estimates of* θ^j *and* ν.

As in Simonovska and Waugh (2014), we use $\theta^j = 4 \;\; \forall j$.[28] Because estimates for ν do not exist, we propose a strategy to estimate its value which will allow us to to take a stand on the correlation structure of productivity draws between ordinary and processing.[29] This parameter is important because it governs *within-industry* comparative advantage between ordinary and processing production, and the potential gains from allowing processing to sell domestically in our counterfactuals. Using the triad strategy of Caliendo and Parro (2015) in conjunction with equations (4) and (6), we

[26] The wage is equal to total wage payments in manufacturing divided by total employment.

[27] Appendix B describes how we measure the cost shares for ordinary and processing production within an industry.

[28] We also set $\sigma^j = 2 \; \forall j$. As in Eaton and Kortum (2002), our results are robust to the choice of σ^j. We examine the robustness of our results to alternate values of θ^j in section 6.

[29] Lind and Ramondo (2018) is a notable exception.

obtain the following expression:

$$\left(\frac{\pi^j_{no}\pi^j_{oh}\pi^j_{hn}}{\pi^j_{nh}\pi^j_{ho}\pi^j_{on}}\right) = \left(\frac{(1+\tau^j_{no})(1+\tau^j_{oh})(1+\tau^j_{hn})}{(1+\tau^j_{nh})(1+\tau^j_{ho})(1+\tau^j_{on})}\right)^{-\theta^j} \left(\frac{s^j_{no}}{s^j_{ho}}\right)^{\nu} \tag{12}$$

where the π^j_{ni} are *across-country market shares*, τ^j_{ni} are statutory tariffs, and s^j_{no} are *within* China shares of exports accruing to ordinary exports $s^j_{no} \equiv \frac{\pi^j_{no}}{\pi^j_{no}+\pi^j_{np}}$. When $\nu = 0$, draws between ordinary and processing are uncorrelated, and equation (12) nests the strategy of Caliendo and Parro (2015). Conditional on θ^j, we can use a simple method of moments strategy to estimate ν.[30]

Using the language of discrete choice models [e.g. Berry (1994)], ordinary and processing trade are assumed to reside within a group. As 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 between the two organizational forms, and leads to a stronger relationship between the *within-group* shares on the right hand side and *across-market* ordinary market shares on the left. Our estimation method 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.[31] To our knowledge, this is the first time such a strategy has been used to estimate the

[30]Unlike Caliendo and Parro (2015), we move the term involving θ^j over to the left hand side in our estimation. We do this for data-related reasons. By 2000, when our China customs data begins, 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 which is the period of the analysis in Caliendo and Parro (2015). In our data at the exporter-importer-ISIC industry-year level in 2000, 80% of reported 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 imply that tariffs cuts do not matter but rather that the triad approach removes much of the meaningful variation post-WTO. Using additional non-China countries in the triad does not add to our ability to identify ν and so we do not pursue this further. We also note that there is broad agreement that θ lies roughly between 4 and 6 even when estimated in models that nest our approach (e.g. Simonovska and Waugh (2014) which does not include China). However we also examine the robustness of our results to alternate values of θ below. When all tariffs are set at MFN rates, ν is still identified as equation (12) becomes $\left(\frac{\pi^j_{no}\pi^j_{oh}\pi^j_{hn}}{\pi^j_{nh}\pi^j_{ho}\pi^j_{on}}\right) = \left(\frac{s^j_{no}}{s^j_{ho}}\right)^{\nu}$.

[31]See Berry (1994), section 5.

correlation parameter in a multi-variate Fréchet distribution.[32] As in Caliendo and Parro (2015), the use of the triad approach differences out all destination-industry-specific, source-industry-specific, and pair-industry-specific factors which mitigates–though not necessarily eliminates–endogeneity concerns.[33]

Where t indexes years, we pool observations across industries j and the years 2000-2007. We then estimate a log-linear equation based on (12):

$$\ln\left(y^j_{noht}\right) = \nu \ln\left(\frac{s^j_{not}}{s^j_{hot}}\right) + \epsilon^j_{noht} \tag{13}$$

where

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

and ϵ^j_{noht} is a white noise error term which is assumed to be normally distributed. The resulting estimate of ν, $\widehat{\nu}$, is 0.72 with a standard error, clustered by noh triplets, of 0.02. The tight estimate allows us to reject both the null hypotheses that $\nu = 0$ and $\nu = 1$ at conventional levels.[34] We examine the importance of heterogeneity in $\widehat{\nu}$ across industries in section 6.

5.2 *Measuring States of Technology*

We estimate states of technology for ordinary and processing production for two reasons. First, we are interested in how differential productivity levels within and across industries affect the

[32]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 or industries 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. Calibration-based approaches to measuring this parameter are found in Arkolakis, Ramondo, Rodríguez-Clare and Yeaple (2018b) and Lagakos and Waugh (2013). Independently of this paper, Lind and Ramondo (2018) develop a two-step gravity-based estimator to identify low- and high-correlation industries using aggregate shipments.

[33]For example, all c^j_i, λ^j_i, and Φ^j_i terms are differenced out as are $g^j(d_{ni})$ and t^j_i. Although pair specific terms are differenced out, pair-*direction*-specific terms such as tariffs τ^j_{ni} remain.

[34]We have also experimented with estimating this expression in first differences between 2000 and 2007, which produces an estimate of 0.64. The difference between the two can result either from classical measurement error whose effect is magnified in first differences or from an error term that is positively correlated with $\ln\left(s^j_{not}/s^j_{hot}\right)$. Using the higher value of $\widehat{\nu}$ increases the correlation of the draws between ordinary and processing and is analogous to making them more substitutable in the context of a CES model reducing the possible welfare gains from allowing processing to sell domestically.

potential gains from allowing processing to sell domestically in our counterfactuals. If processing expands the most in industries in which it has relatively higher productivity, this is similar to classic productivity-based comparative advantage and our counterfactual has the intuitive interpretation as measuring Ricardian gains from domestic market liberalization.[35] Second, when examining the contribution of productivity growth in explaining the changes in ordinary exports vis-à-vis processing, we need to know by how much ordinary and processing productivity increased.

To do this, we follow the structural gravity approach of Levchenko and Zhang (2016). First, we estimate a gravity model for each industry and year. The resulting country-industry fixed effects measure differences in unit costs. Using factor prices, which are available as described in section 4, and intermediate input prices obtained using the structure of the model, we can isolate $\lambda_n^j/\lambda_{us}^j$ for all countries and industries including ordinary and processing in China.

5.21 *Measuring $\lambda_n^j/\lambda_{us}^j$ outside of China, and for Ordinary Production*

In what follows, we suppress the year subscript although all estimation occurs at the industry-year level. 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

$$\ln\left(\frac{\pi_{ni}^j}{\pi_{nn}^j}\right) = \ln\left(\lambda_i^j\left[c_i^j\right]^{-\theta^j}\right) - \ln\left(\lambda_n^j\left[c_n^j\right]^{-\theta^j}\right) - \theta^j \ln\left(\kappa_{ni}^j\right). \tag{14}$$

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 these trade costs as in Eaton and Kortum (2002), Waugh (2010), and Levchenko and Zhang (2016): $\theta^j \ln\left(\kappa_{ni}^j\right) \equiv \theta^j \ln(1+\tau_{ni}^j) + \sum_{d=1}^6 \beta_d^j d_{ni,d} + b_{ni}^j + \delta_i^{j,x} + \epsilon_{ni}^j$ where $d_{ni,d}$ is an indicator variable that takes a value of one when the distance between countries n and i is in the d^{th} distance interval.[36] β_d^j is the industry-year-specific effect of being in interval d. b_{ni}^j is the industry-specific effect of sharing a border. $\delta_i^{j,x}$ is a dummy variable that takes a value of one when i is an exporting country for industry j. When $i \neq o,p$, then

[35] ν governs within-industry comparative advantage gains, and differences in λ_p^j/λ_o^j across industries govern across-industry comparative advantage gains.

[36] Intervals are in miles: [0,375); [375,750); [750,1500); [1500,3000); [3000,6000); and [6000,maximum].

$\delta_i^{j,x} \equiv \theta^j \ln(t_i^j)$. For $i = o$ and $i = p$, respectively,

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

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

The extra terms for China reflect the correlated Fréchet draws.[37] Since π_{pp}^j=0, equation (15) is undefined when $n = p$, and shipments for processing only show up as exports. Consequently, the industry-specific fixed effect for processing does not identify its unit cost. We discuss how to measure $\lambda_p^j/\lambda_{us}^j$ shortly.

Moving observed tariffs to the left hand side of (14) delivers the following gravity regression where δ_i^j is a country fixed effect within a given industry-level regression:[38]

$$\ln\left(\frac{\pi_{ni}^j}{\pi_{nn}^j}\right) + \theta^j ln(1+\tau_{ni}^j) = \delta_i^j - \delta_n^j - \sum_{d=1}^{6}\beta_d^j d_{ni,d} - b_{ni}^j - \delta_i^{j,x} + \epsilon_{ni}^j \tag{15}$$

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

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

$$\exp\left(\frac{\widehat{\delta}_i^j}{\widehat{\delta}_{us}^j}\right) = \frac{\lambda_i^j}{\lambda_{us}^j}\left(\frac{c_i^j}{c_{us}^j}\right)^{-\theta^j}. \tag{16}$$

In this type of analysis, 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.[39] This allows recovery of estimates of $\lambda_i^j/\lambda_{us}^j$.

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

[38] There are two reasons for moving the term involving tariffs to the left hand side: First, because of concerns about the endogeneity of tariffs; and second, because of widespread agreement about values of θ^j. In the robustness section, when we examine our results with respect to alternate values of θ^j, we also change its value in this estimation stage.

[39] See Waugh (2010) at the national level and Levchenko and Zhang (2016) at the country-industry level.

However, it is not obvious 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 (16) as

$$exp\left(\frac{\widehat{\delta}_i^j}{\widehat{\delta}_{us}^j}\right) = \frac{\lambda_i^j}{\lambda_{us}^j}\left[\left(\frac{w_i}{w_{us}}\right)^{\tilde{\gamma}_{l,i}^j}\left(\frac{r_i}{r_{us}}\right)^{\tilde{\gamma}_{k,i}^j}\Pi_{k=1}^{J+1}\left(\frac{p_i^k}{p_{us}^k}\right)^{\tilde{\gamma}_i^{kj}}\right]^{-\theta^j} \tag{17}$$

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.[40] While this calculation is general up to a translog approximation, when we move to our counterfactual analyses, we assume that factor 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 counterfactual simulations rely on more restrictive assumptions than our productivity calculations.

Equation (17) 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 4, and, following Simonovska and Waugh (2014), we use a constant value of $\theta = 4$ for θ^j. This leaves us requiring empirical counterparts of $\frac{p_i^k}{p_{us}^k}$ to obtain empirical counterparts of $\frac{\lambda_i^j}{\lambda_{us}^j}$ which we obtain following Shikher (2012) and Levchenko and Zhang (2016).[41]

[40]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.

[41]To obtain these, take the ratio of π_{ii}^j and $\pi_{us,us}^j$, and equation (8) 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 (17) to obtain the empirical counterpart of p_n^k/p_{us}^k, $\widehat{p_n^k/p_{us}^k}$, in terms of data, $\pi_{ii}^j/\pi_{us,us}^j$, and previously estimated values $\frac{\widehat{\delta}_i^j}{\widehat{\delta}_{us}^j}$: $\left(\widehat{p_i^j/p_{us}^j}\right)^{\theta^j} = (\pi_{ii}^j/\pi_{us,us}^j)/\left[\exp\left(\hat{\delta}_i^j/\hat{\delta}_{us}^j\right)\right]$. With these in hand, we can easily calculate $\Pi_{k=1}^{J+1}\left(\frac{\widehat{p}_i^k}{\widehat{p}_{us}^k}\right)^{\tilde{\gamma}^{kj}}$, and obtain values of $\lambda_i^j/\lambda_{us}^j$ from equation (17). To interpret total factor productivity as a cost-shifter relative to the US, our preferred measure of productivity is given by $\left(\lambda_i^j/\lambda_{us}^j\right)^{\frac{1}{\theta^j}}$. See Appendix D for details of how to construct the price index for non-traded goods.

5.22 $\lambda_p^j/\lambda_{us}^j$

Obtaining productivity for processing in China requires a little more work. If we set $t_o^j = t_p^j$ and exponentiate $\widehat{\delta}_o^j$, $-\widehat{\delta}_o^{j,x}$, and $-\widehat{\delta}_p^{j,x}$, we obtain:

$$\frac{\exp\left(\widehat{\delta}_o^j\right)\exp\left(\widehat{-\delta}_o^{j,x}\right)}{\exp\left(\widehat{-\delta}_p^{j,x}\right)} = \left(\frac{\lambda_o^j}{\lambda_p^j}\right)^{\frac{1}{1-\nu}}\left(\frac{c_o^j}{c_p^j}\right)^{-\frac{\theta^j}{1-\nu}}. \tag{18}$$

Because labor and capital are mobile across sectors, factor prices cancel between the numerator and denominator of c_o^j/c_p^j but we still require an empirical counterpart for $\Pi_{k=1}^{J+1}\left(\frac{p_p^k}{p_o^k}\right)^{\tilde{\gamma}^{kj}}$. We can use equation (8) for ordinary and processing, and then manipulate the resulting expression to deliver the price index for processing relative to ordinary:

$$\frac{p_p^j}{p_o^j} = \left[\pi_{oo}^j + \sum_i^N (1+\tau_{oi}^j)^{\theta^j}\pi_{oi}^j\right]^{-\frac{1}{\theta^j}}. \tag{19}$$

This is a function of observable data (trade shares and tariffs), and the parameter θ^j. This expression has the intuitive interpretation that the difference in price indexes between ordinary and processing is related to a weighted average of tariffs imposed on ordinary but not processing imports into China.

6. Results

There are three key components of our analysis: the estimation of the gravity model, estimates of total factor productivity in processing and ordinary, and finally, our counterfactuals. We discuss each in turn.

6.1 Gravity Model

The first step in our empirical approach is to estimate a gravity model for each industry-year pair jt. This amounts to estimating equation (15) for each of the 109 industries and years in 2000-2007. The estimated equations fit the data very well: for 109 estimated equations in the year 2000, the mean and median R^2 are 0.961 and 0.968, respectively.[42] Overall, consistent with previous work, we find that the log-linear gravity specification with country-industry fixed effects fits the data extremely well.

6.2 Productivity

Several recent papers examine productivity differences between ordinary and processing firms and find lower productivity growth within an industry in processing: Yu (2015), Manova and Yu (2016), Dai et al. (2016). One potential explanation for this behavior is negative selection into processing resulting from the preferential treatment extended to processing firms.[43] These differences may also be due to data issues that make estimation of TFP under the two regimes difficult. Significantly, differences in tariff treatment, transfer pricing, as well as the destination (origin) of output (inputs) give rise to differences in the behavior of output and input prices between the two forms. As a result, the use of a common set of deflators is problematic, and estimates of productivity in levels as well as growth are potentially biased.[44] While more restrictive in some dimensions (e.g. market structure), our approach allows progress on these issues. First, by inverting unit costs from expenditure share data, we mitigate issues of output price measurement. Second, we explicitly take into account differences in input prices paid by ordinary and processing producers due to how imported intermediate inputs are treated.[45]

Table 1 reports summary statistics for TFP for ordinary and processing relative to the US (and relative to each other) for 2000 and 2007. The first row shows that the (unweighted) average productivity in ordinary production in China was approximately 40% of the US and productivity in processing only slightly lower. Within industries (row 3), processing was approximately 5%

[42]The minimum is 0.875 and the maximum is 0.995. The mean value for the estimated coefficient on each dummy variable for distance is monotonically decreasing for the six intervals in increasing order of distance. The effect of sharing a border is positive for 105 out of 109 industries.

[43]Controlling for industry fixed effects, these papers find that processing exporters are on average less productive than ordinary exporters. These papers ignore heterogeneity across industries, which may be a source of comparative advantage.

[44]Using detailed data on physical quantities for a single sector (leather shoes) Li, Smeets and Warzynski (2017) find higher productivity in processing than ordinary.

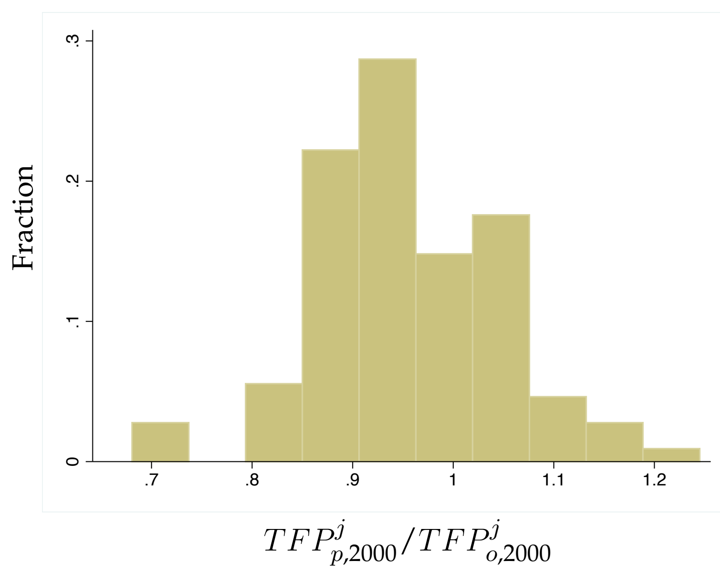
[45]See equation (19).

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

Variable	N	Mean	sd	min	max
$TFP^j_{o,2000}$	109	0.398	0.176	0.074	1.623
$TFP^j_{p,2000}$	108	0.383	0.186	0.079	1.636
$TFP^j_{p,2000}/TFP^j_{o,2000}$	108	0.956	0.092	0.681	1.245
$TFP^j_{o,2007}$	109	0.527	0.181	0.186	1.200
$TFP^j_{p,2007}$	109	0.507	0.193	0.186	1.258
$TFP^j_{p,2007}/TFP^j_{o,2007}$	109	0.957	0.078	0.770	1.296

Notes: This table presents measures of total factor productivity for ordinary and processing production as represented by $(\widehat{\lambda^j_{o,t}/\lambda^j_{us,t}})^{\frac{1}{\theta}}$ and $(\widehat{\lambda^j_{p,t}/\lambda^j_{us,t}})^{\frac{1}{\theta}}$. These estimates are created using the procedure described in section 5 and a value of $\theta^j = 4$ for all j. All values are relative to the US.

Figure 1: Histogram of $TFP^j_{p,2000}/TFP^j_{o,2000}$



Notes: This table presents a histogram of $TFP^j_{p,2000}/TFP^j_{o,2000}$ calculated as described in the text setting $\theta^j = 4\,\forall j$.

Table 2: Total Factor Productivity in China: Ordinary and Processing Production (Levels, Weighted)

Variable	**N**	**mean**	**sd**	**min**	**max**
$TFP^j_{o,2000}$	109	0.471	0.241	0.074	1.623
$TFP^j_{p,2000}$	108	0.607	0.400	0.079	1.636
$TFP^j_{p,2000}/TFP^j_{o,2000}$	108	0.947	0.098	0.681	1.245
$TFP^j_{o,2007}$	109	0.600	0.138	0.186	1.200
$TFP^j_{p,2007}$	109	0.693	0.255	0.186	1.258
$TFP^j_{p,2007}/TFP^j_{o,2007}$	109	0.936	0.086	0.770	1.296

Notes: This table presents measures of total factor productivity for ordinary and processing production as represented by $(\widehat{\lambda^j_{o,t}/\lambda^j_{us,t}})^{\frac{1}{\theta}}$ and $(\widehat{\lambda^j_{p,t}/\lambda^j_{us,t}})^{\frac{1}{\theta}}$. These estimates are based on the procedure described in section 5 and use a value of $\theta^j = 4$ for all j. All values are relative to the US. Observations are weighted by total industry ordinary shipments for ordinary productivity, total industry processing exports for processing productivity, and total industry shipments for relative measures.

less productive on average. However, there is substantial heterogeneity around that mean with a minimum-maximum interval of [-31.9%,+24.5%]. The histogram in Figure 1 captures this heterogeneity.[46] Our finding that processing is slightly less productive is in line with previous findings (e.g. Yu (2015), Manova and Yu (2016), and Dai et al. (2016)). However, our finding of substantial heterogeneity and the fact that processing sectors often have a comparative advantage over ordinary is new and essential to gains from allowing processing firms to sell domestically. The bottom three rows of Table 1 reveal that ordinary and processing narrowed the gap in productivity vis-à-vis the U.S. at similar rates from 2000 to 2007, while within sectors, productivity differences between the two forms were unchanged on average.

Weighting by industry size (Table 2), processing's advantage in certain large sectors emerges: processing productivity in 2000 was 61% of the US level while ordinary productivity was 47%. Between 2000 and 2007, we observe some convergence in productivity between the two, with ordinary's mean productivity rising to 60% of the US compared to 69% for processing. There are

[46]The four ISIC sectors in which the processing premium is the lowest are Tobacco (1600), Motor Vehicles (3410), Cement/Lime/Plaster (2694), and Weapons (2927). The four sectors for which it is the highest are Office and Computing Machinery (3000), Bodies for Motor Vehicles (3420), Steam Generators (2813), and Watches and Clocks (3330).

Table 3: Total Factor Productivity in China: Ordinary and Processing Production (Growth)

variable	N	mean	sd	min	max
$TFP^j_{o,2007}/TFP^j_{o,2000}$	109	1.378	0.305	0.566	2.608
$TFP^j_{p,2007}/TFP^j_{p,2000}$	108	1.384	0.280	0.580	2.464

Notes: This table presents cumulative growth for total factor productivity relative to the United States for ordinary and processing production. These estimates are constructed using the procedure described in section 5 and a value of $\theta^j = 4$ for all j.

two potential reasons for this behavior: first, productivity in ordinary grew fastest in those sectors in which it was initially less productive than processing; and second, sectors in which relative TFP for ordinary was initially highest grew the most rapidly.

Table 3 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 (2017a)], 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).[47]

Why might these differences in productivity exist? Processing commonly entails the labor-intensive assembly of products with high-import content [e.g. Kee and Tang (2016), Koopman, Wang and Wei (2012)]. A foreign partner usually assumes responsibility for design, management of the supply chain, and logistics. Local firms largely oversee the labor-intensive assembly and ensure quality levels and the timely delivery of output, while keeping final costs down. In contrast, firms involved in ordinary production typically require a much broader set of capabilities that span design, local sourcing, manufacturing, and logistics. These differences in firms' abilities to use high quality inputs, design goods, and manage supply chains can lead to measurable differences in productivity between ordinary and processing production. Even more simply, higher levels of multinational activity in processing suggest that foreign affiliates may be bringing different states of technology to China.

[47] Our estimates of TFP growth in processing and industry are relative to the US. Adding the productivity growth in the US over this period implies productivity growth on the order of 6% per annum. This compares with aggregate TFP growth of 5.1% as measured by the Penn World Tables, which is consistent with lower measured TFP growth in services during this period.

Table 4: Real Wages and Income: Counterfactual Simulations

Specification Number	Processing Specification Description	Real Wage (rel. to US) (1)	Real Factor Income (rel. to US) (2)	Real Income (rel. to US) (3)
(1)	Benchmark	1.000	1.000	1.000
(2)	No exemption	0.999	1.000	1.000
(3)	No exemption, sells domestically	1.069	1.033	1.027
(4)	Sells domestically	1.073	1.036	1.027
(5)	No Processing	0.985	0.995	0.994

Notes: Row (1) represents the baseline equilibrium in which actual values of productivity and tariffs are imposed and processing is not allowed to sell domestically. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do: $\tau^j_{pn} = \tau^j_{on}\ \forall\ j,n$. Row (3) allows processing firms to sell to the ordinary sector and to the processing sector but loses their tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$ and $\tau^j_{pn} = \tau^j_{on}\ \forall\ j,n$. Row (4) is the same as row (3) but processing keeps its tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$. Row (5) imposes infinite trade costs on all shipments out of the processing sector: $\kappa^j_{np} = \infty\ \forall j,n$. Real factor income=wage+capital income. Real income=wage+capital income+tariff revenue. $\theta^j = 4$ and $\nu = 0.72$.

6.3 *Counterfacuals: The Welfare Effects of Processing*

Before assessing the welfare impacts of processing, we briefly assess model fit by comparing the raw data to model-generated data using our estimated parameters to solve for a baseline equilibrium.[48] As suggested by the high R^2 statistics from the gravity model estimation, π^j_{ni} and its model-generated counterpart, $\widehat{\pi}^j_{ni}$, are highly correlated. The correlation between the two is 0.90 and the slope coefficient from a regression of $\widehat{\pi}^j_{ni}$ on π^j_{ni} is 0.84.[49] Because of our interest in ordinary relative to processing trade, we also examine the model-implied share of aggregate exports through processing trade. In the data in 2000, this share was 60% while the model delivers 59%. This is reassuring given that this moment is not directly targeted in our estimation.[50]

Processing is not a single policy lever: it combines several instruments each of which has potentially different welfare effects. For this reason, our counterfactuals examine the effect of each

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

[49] The coefficient on a reverse regression of π^j_{ni} on $\widehat{\pi}^j_{ni}$ is 0.97.

[50] Specifically, we compare $\frac{\sum_{i,j} X^j_{ip}}{\sum_{i,j}\left[X^j_{io}+X^j_{ip}\right]}$ to $\frac{\sum_{i,j} \widehat{X}^j_{ip}}{\sum_{i,j}\left[\widehat{X}^j_{io}+\widehat{X}^j_{ip}\right]}$. 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.

individual policy in isolation and also in combination with the other policy measures. As criteria for welfare, we calculate real wages, real factor (labor and capital) income, and real income (factor income plus tariff revenue). Each comparison is relative to the United States. The first row of Table 4 calculates these outcomes in a benchmark model that uses the actual values of productivity and tariffs for 2000 and in which processing cannot sell domestically. For ease in interpreting counterfactual welfare effects in the rows that follow, we normalize each baseline outcome to one.

Row 2 examines the benefit from the duty-free treatment of processing by calculating welfare if processing were subject to the same tariffs as ordinary production (i.e. processing loses its duty exemption).[51] The full set of general equilibrium interactions is complex and priors are not obvious. For example, Panagariya (1992) argues that the welfare effects of the introduction of full duty drawbacks for exports is ambiguous when there are tariffs elsewhere in the economy. Looking at columns (1)-(3), real wages fall slightly while real factor income and real total income increase marginally. These small changes reflect the relatively small share of processing exports in gross manufacturing output, which is on the order of $\approx 10\%$, and is consistent with the relatively small effects of incremental trade liberalization found in Eaton and Kortum (2002).

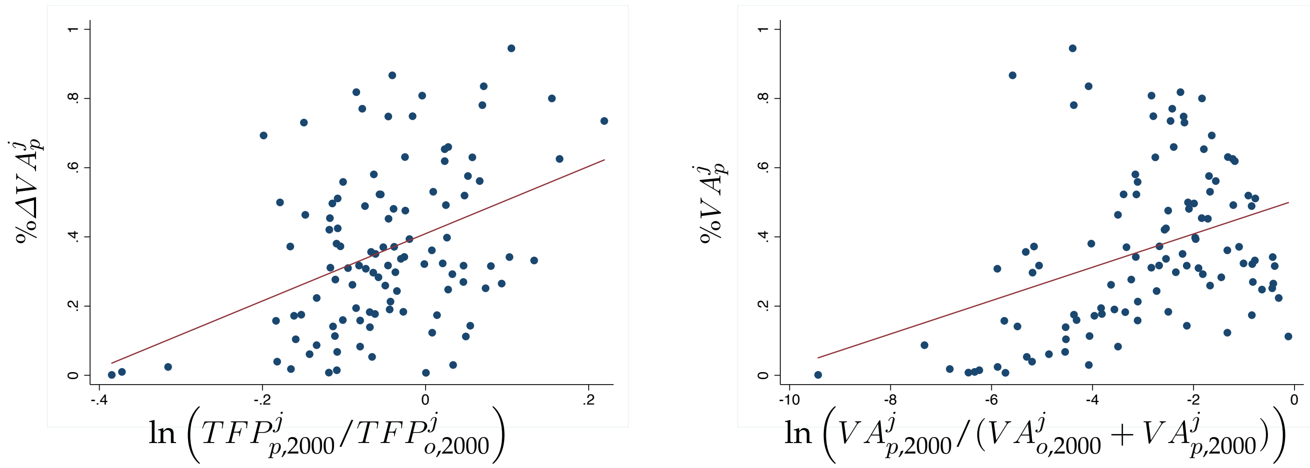
Our second counterfactual experiment focuses on the other major policy component of processing: the restriction from selling to domestic agents. Row 3 of Table 4 presents our results for the counterfactual in which processing producers can sell to domestic consumers but lose their tariff exemption. Specifically, we impose $\kappa_{pp}^{j} = \kappa_{op}^{j} = 1$ and $\tau_{pn}^{j} = \tau_{on}^{j}\ \forall\ j,n$. Differences in productivity between the two forms of organization are important for understanding this counterfactual. Less than perfectly correlated productivity draws and different states of technology introduce the possibility of welfare gains due to comparative advantage both within and across industries.[52]

We find major welfare effects. In the context of our model, real wages rise by 6.9% in a coun-

[51] More precisely, we set $\tau_{pn}^{j} = \tau_{on}^{j}$ instead of setting $\tau_{pn}^{j} = 0$ as in the benchmark case (row 1).

[52] An assumption implicit in the framework upon which we draw is that production is irreversibly pre-committed to either ordinary or processing. For example, if 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.

Figure 2: Counterfactual Growth of Processing Across Industries



Notes: The panel on the left presents the proportional change in processing value added between the counterfactual in row (3) and row (1) of table 4 on the vertical axis and $\ln\left(TFP^j_{p,2000}/TFP^j_{o,2000}\right)$ calculated in table 1 on the horizontal axis. Each dot represents an industry. The line is an OLS best fit with a coefficient of 0.92 and a bootstrapped t-statistic of 4.44. These results are invariant to the two data points in the lower left corner. The panel on the right also plots the counterfactual change in value added on the vertical axis but plots the benchmark (log) initial share of value added in the industry accruing to processing on the horizontal axis. The line is an OLS best fit with a coefficient of 0.048 and a bootstrapped t-statistic of 4.24.

terfactual world in which Chinese consumers can buy from processing producers but processing loses its tariff exemption. Several factors are responsible for such a large increase. First, processing production is more labor intensive than ordinary production.[53] Second, because of transportation costs, consumers spend a much larger share of their incomes on domestically provided goods than imported goods. Consequently, any policy affecting the menu of prices offered by domestic producers will have a much larger effect than a policy that affects the prices charged on imports. In this counterfactual, processing grows from 13% to 45% of gross manufacturing output. The second column shows that real factor income grows by less (3.3%), reflecting that the gains for labor are larger than the gains to capital. Finally, real total income grows by slightly less than total factor income. This is because increased domestic sales by processing crowd out imports, and tariff revenue falls despite the elimination of a duty drawback in this counterfactual.

Figure 2 helps illustrate the mechanism behind these results. On the left, we graph the percentage

[53] The mean of $\gamma^j_{l,o}$ is 0.04 while the mean of $\gamma^j_{l,p} = 0.08$.

change in industry value added in processing under the counterfactual (relative to the benchmark) against relative productivity in processing in 2000. Each dot represents an industry. The fact that all points are above the origin shows that processing expands in *all* industries with the new access to the domestic market. The strong upward sloping relationship suggests that gains from relaxing the restriction are greatest in those sectors in which processing is most productive relative to ordinary.[54] The panel on the right plots the same change in industry value added in processing but against processing's (model) value added share in 2000. The upward sloping relationship shows that industries in which processing was more important in 2000 also grew most under the counterfactual.

Row (4) shows that these welfare effects are even larger when processing is allowed to keep its duty drawback. Real wages, real factor income, and real total income increase by 7.3%, 3.6%, and 2.7% respectively. While these incremental increases relative to row (3) are small, they are also consistent with the small gains from processing's tariff exemption in row (2). Finally, row (5) considers the complete dismantling of the processing regime by setting $\kappa^j_{ip} = \infty \; \forall i,j$. This differs from row (3) in that no Chinese firms organize through processing and all comparative advantage gains–both within- and across-industry–are eliminated. The welfare losses in this counterfactual show that differential productivity levels between ordinary and processing both within and across industries are a source of comparative advantage.

6.31 The Welfare Effects of Processing: Robustness

We now assess the robustness of our results in a number of ways. First, we allow for heterogeneity in θ^j as suggested by Caliendo and Parro (2015). Second, we allow for industry-level heterogeneity in our estimated parameter ν. Third, we recalculate the welfare effects of processing when the draws between ordinary and processing are independent, i.e. $\nu = 0$, while still allowing the location parameters λ_o and λ_p to differ. This counterfactual offers guidance on the bias introduced by assuming uncorrelated productivity draws rather than explicitly modeling them using a multivariate

[54] Industries contributing significantly to the increase in processing's share of total exports include apparel, plastics, furniture, printing, and paper and paper products.

Fréchet distribution. A final counterfactual takes as its benchmark a setting in which "roundabout" shipping exists. In this setting, processing firms can access the domestic market by first shipping to a foreign country and then shipping the good back into China. We discuss the results below but relegate all tables to the Appendix.

We first replicate our results from Table 4 but impose the values of θ^j estimated in Caliendo and Parro (2015).[55] These appear in Table 7 in the appendix. The equilibrium in which Chinese consumers and producers can frictionlessly purchase from processing producers entails 5.6% higher real wages and 2% higher real income than the baseline equilibrium in which they cannot.[56] These alternative values of θ^j do not appear to affect our results.

Next, we examine how industry heterogeneity in ν affects our results. To do this, we estimate a value of ν^j for each industry at the two-digit ISIC level using equation (13). Table 8 presents estimates $\hat{\nu}^j$ across 20 industries. We reject the null of zero for all of them. For four industries, the point estimate is greater than one but we cannot reject that they are less than one at p=0.05. Table 9 presents our counterfactual simulations following the same format as Table 4. Again, our welfare effects change little and are only slightly larger than in the primary specifications. Real wages, real factor income, and real total income increase by 8.4%, 3.3%, and 3.3% when processing is allowed to sell domestically but loses its duty drawback.

We next examine the importance of using the multivariate Fréchet distribution relationship relative to a model in which ordinary and processing draws are assumed to be uncorrelated. For this, we set $\nu = 0$ and $\theta^j = 4$ for all industries. This maximizes heterogeneity between the two organizational forms, and the possible gains from allowing processing to sell domestically. Table 10 presents these results. Importantly, we find that assuming that Fréchet draws are uncorrelated between ordinary and processing leads us to overestimate the welfare gains from allowing processing to sell domestically by between 80% and 230%. This suggests that more careful consideration

[55]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.

[56]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.

of the underlying correlation structure of productivity draws across countries may have important welfare implications as in Lind and Ramondo (2018).

Finally, Table 11 considers a set of counterfactuals relative to a baseline that includes the possibility of "roundabout" shipping. In this alternate baseline, processing can ship its goods out of China to the nearest destination (Hong Kong), re-enter, and sell on the domestic market after having incurred the appropriate transport costs and import duties to access the domestic market. In reality, this seems very rare. Customs data records re-imports of processing goods from China and back into China. While China is a relatively large source of processing imports into China (6.7%), far fewer of its ordinary imports (0.7%) are listed as coming from China.[57] Appendix F describes how data are constructed in this case. As suspected, the welfare gains are smaller but still positive (1-4%) with the option of roundabout shipping, and larger than the welfare effects of the duty-drawbacks. The distributional effects are also the same as under the original counterfactual.

6.4 Counterfacuals: The Organization of Trade

In a final 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 ordinary trade. A small literature has examined the determinants of the increasing share of Chinese exports organized through ordinary vis-à-vis processing trade between 2000 and 2007. Brandt and Morrow (2017) argue that falling levels of protection on intermediate inputs and capital equipment as well as an increased desire to access domestic markets were major contributors as each provided agents with a diminishing incentive to organize through processing. Manova and Yu (2016) argue that financial constraints were also important in explaining this evolution. Both assessments rely on reduced form estimation that cannot identify aggregate effects nor provide structural interpretation of the reduced form parameters.

We examine the evolution of the aggregate share of exports organized through ordinary trade

[57]For the vast majority of these shipments, the transfer country is listed as Hong Kong.

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.

through a set of well-defined quantitative experiments.[58] 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, an effect that is not identified in reduced form econometric work. Second, by exploiting our productivity measures derived in section 6.2, we examine the effect of changing productivity levels in upstream sectors in China on sourcing decisions and production costs in ordinary and processing.

Table 5 presents raw data and shows that, in 2000, a little more than 60% of Chinese exports to the countries in our sample were conducted through processing trade and, by 2007, this share had fallen approximately 17% (10.3 percentage points) to 50.6%.[59]

Table 6 presents our counterfactual simulations. In each row, the second column describes the set of tariffs used for the counterfactual. For example, $\widehat{\tau}^j_{oi,2007} = \tau^j_{oi,2007}$ sets Chinese tariffs at their 2007 level and $\widehat{\tau}^j_{oi,2007} = \tau^j_{oi,2000}$ holds tariffs constant at their 2000 levels. The third and fourth columns state which set of productivity estimates are used. The final column presents counterfactual calculations of the share of processing in total exports. All other parameters are held at their 2000 levels in all specifications.

Row 1 holds tariffs and productivity constant at their 2000 level. The predicted aggregate share of exports organized through processing trade (0.593) is very similar to the actual share

[58]Because of assumptions of constant returns to scale and perfect competition, domestic market size does not play a direct role in the organization of trade. Motivated by a model of firm heterogeneity, imperfect competition, and increasing returns to scale, Brandt and Morrow (2017) find evidence that domestic market size affects the firms' decisions about how to organize their trade.

[59]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 than for exports to the entire world.

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

Specification Number	$\widehat{\tau}^j_{oi,2007}$	$\widehat{\lambda}^j_{o,2007}$	$\widehat{\lambda}^j_{p,2007}$	$\frac{\sum_{j,i}\widehat{X}^j_{ip,2007}}{\sum_{j,i}\widehat{X}^j_{ip,2007}+\widehat{X}^j_{io,2007}}$
(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 6.4. The first column states the level that tariffs take in 2007 in China in the simulation. The second column states the level of the state of technology that ordinary sector takes in 2007 in the simulation. The third column states the level of the state of technology that processing sector takes in 2007 in the simulation. The fourth column reports 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.

(0.609). Row 2 uses actual tariff changes in China while holding all productivity terms constant.[60] Lower levels of protection imply lower levels of input tariffs and a weaker incentive for China's exports to be organized through processing trade. Consistent with this idea, our model implies that approximately 26% of the total change in processing exports (2.7 percentage points) can be explained by lower tariffs in China.[61]

The third row keeps tariffs constant at their 2000 level but feeds into the model the observed change in productivity. Differences in productivity growth in ordinary relative to processing trade can explain approximately 64% (6.6 percentage points) of the observed change. As Chinese capabilities increase, ordinary production benefits most as it relies more on domestically provided intermediate inputs [e.g. Kee and Tang (2016)]. In addition, as ordinary productivity increases relative to processing (Table 2), ordinary obtains larger market shares on each external market. Row 4 considers the effect of both lower tariffs and the observed changes in productivity for the size of the ordinary and processing sectors. Combined, lower levels of protection and observed

[60]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.

[61]While their focus is on aggregate Chinese exports, Liu and Ma (2018) find similar evidence using a model of firm heterogeneity and worker/firm migration. They do not explicitly consider the role of changing productivity levels either in aggregate or across ordinary and processing production.

changes in productivity growth are consistent with the changes we observe in trade shares.

In summary, lower levels of protection appear to have increased the share of ordinary trade in total exports between 2000 and 2007. However, they are only able to explain slightly more than a quarter of the total change. Far more important are improvements in underlying productivity, which explain nearly two-thirds of the total change.[62]

7. Conclusion

Export processing zones and processing activities 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 less common. 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 assess the quantitative importance of two common characteristics of processing regimes: export processing producers do not have to pay duties on imported intermediate inputs 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, we find significant differences across industries in relative productivity between ordinary and processing. Second, the welfare effects of duty drawbacks are not quantitatively large. This is in line with other work suggesting that the gains from incremental trade liberalization are small e.g. Eaton and Kortum (2002) and Caliendo and Parro (2015). And 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 domestic market liberalization allows for a new form of gains from trade.

Processing is often thought to entail benefits such as foreign exchange accumulation and learning-by-doing. These do not show up in our model, but in light of our estimates of the welfare

[62] The sum of the counterfactuals changing tariffs *or* productivity levels is not equal to the effect of changing both due to general equilibrium effects. In other words, these two numbers should not be considered a decomposition.

losses tied to the constraints on producing producers, they must be large in order to justify the current processing regime. However, this raises the issue of optimal policy: Is there an alternative set of policies that can encourage foreign exchange and knowledge accumulation that does not entail the costly distortions that come from prohibiting processing producers to sell domestically?

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Appendix A. Proofs

A.1 Price Distributions

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

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

Using the properties of the Fréchet, 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 Fréchet 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.1.1 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.1.2 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 producers 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

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

A.1.3 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 producers in China. Therefore, the distribution of prices in the Chinese processing sector is given by

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

where

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

A.2 Expenditure Shares

A.2.1 Non-China Sources, Non-China Destinations

For non-China destinations, expenditure shares π_{ni}^j are straightforward applications of the Fréchet 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

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

A.2.2 Non-China Sources, China as a Destination

Because ordinary agents cannot purchase processing output, the share of expenditure by ordinary producers on goods from 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:

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

A.2.3 Chinese Ordinary Exports to Non-China Destinations

For this section, it helps to define two small pieces of additional notation. First, denote the minimum productivity level that a Chinese ordinary exporter must have so that his delivery price of a given variety in industry j and market n 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

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

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 sourced from Chinese ordinary sector is cheaper than that sourced from Chinese processing sector *and* also that from 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

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

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

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

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

where the second equality follows from the distribution function (A6). Substitute in $\mu^j_n=\frac{c^j_o\kappa^j_{no}}{c^j_p\kappa^j_{np}}$ 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 $\frac{\lambda_o^{j\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}}{\lambda_o^{j\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}+\lambda_p^{j\frac{1}{1-\nu}}(c^j_p\kappa^j_{np})^{-\frac{\theta^j}{1-\nu}}}$ captures the relative size of ordinary trade in market nj. It is higher when the productivity of ordinary trade is relative higher, or relative cost of ordinary trade is lower. The second term $\frac{[\lambda_o^{j\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}+\lambda_p^{j\frac{1}{1-\nu}}(c^j_p\kappa^j_{np})^{-\frac{\theta^j}{1-\nu}}]^{1-\nu}}{[\lambda_o^{j\frac{1}{1-\nu}}(c^j_o\kappa^j_{no})^{-\frac{\theta^j}{1-\nu}}+\lambda_p^{j\frac{1}{1-\nu}}(c^j_p\kappa^j_{np})^{-\frac{\theta^j}{1-\nu}}]^{1-\nu}+\sum_{i\neq o,p}\lambda^j_i(c^j_i\kappa^j_{ni})^{-\theta^j}}$ captures the market share of China as a whole in market nj.

A.2.4 Chinese Processing Exports to Non-China Destinations

Similarly, the expenditure share on goods from processing sector is

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

A.3 Market Clearing

Because income equals expenditure:

$$\sum_{j=1}^{J+1}\sum_{i=1}^{N+2}X^j_n\frac{\pi^j_{ni}}{1+\tau^j_{ni}}=\sum_{j=1}^{J+1}\sum_{i=1}^{N+2}X^j_i\frac{\pi^j_{in}}{1+\tau^j_{in}}. \tag{A8}$$

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 also holds for China based on ordinary and processing trade:

$$\sum_{j=1}^{J+1}\sum_{i=1}^{N+2} X_o^j \frac{\pi_{oi}^j}{1+\tau_{oi}^j} + \sum_{j=1}^{J+1}\sum_{i=1}^{N+1} X_p^j \pi_{pi}^j = \sum_{j=1}^{J+1}\sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{1+\tau_{io}^j} + \sum_{j=1}^{J+1}\sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{1+\tau_{ip}^j} \tag{A9}$$

Outside of China, aggregate factor payments are given by:

$$\sum_{j=1}^{J+1} \gamma_{l,n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} = w_n L_n \qquad \text{and} \qquad \sum_{j=1}^{J+1} \gamma_{k,n}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j} = r_n K_n. \tag{A10}$$

For China, these expressions are

$$\sum_{j=1}^{J+1} \gamma_{l,o}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{1+\tau_{io}^j} + \sum_{j=1}^{J} \gamma_{l,p}^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{1+\tau_{ip}^j} = w_c L_c \tag{A11}$$

and

$$\sum_{j=1}^{J+1} \gamma_{k,o}^j \sum_{i=1}^{N+2} X_i^j \frac{\pi_{io}^j}{1+\tau_{io}^j} + \sum_{j=1}^{J} \gamma_{k,p}^j \sum_{i=1}^{N} X_i^j \frac{\pi_{ip}^j}{1+\tau_{ip}^j} = r_c K_c \tag{A12}$$

Appendix B. Data Appendix

B.1 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.2 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.

B.3 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 are 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.[63]

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 construct 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 these 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 118 industries. On average, the remaining countries in the data set have 94/118 industries.

Cobb-Douglas consumption shares are from the WIOD data that provide 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 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 let 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:

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

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

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.

B.4 Estimating $\alpha_{l,o}^j$, $\alpha_{k,o}^j$, $\alpha_{l,p}^j$, and $\alpha_{k,p}^j$

The Chinese manufacturing data collected by NBS do not include inputs by organization of production. Because most four-digit ISIC industries in China have strictly positive ordinary *and* processing exports, this means that input data are pooled across organization forms. However, we wish to obtain cost shares for ordinary and processing separately within an industry. We describe here our procedure for obtaining these measures. First, we use the linked Customs to firm-level data that are a product of annual surveys by the National Bureau of Statistics (NBS). This dataset has been used extensively in the China trade literature [e.g. Kee and Tang (2016) and Brandt and Morrow (2017)]. This results in a sub-sample that covers 32 percent of the aggregate export value in 2000 and 37 percent in 2006. We then map the Chinese CIC industrial classification codes to ISIC industries as used in this paper. Let f index $f$irms. At the firm-level we calculate the wage share of output as well as the share of intermediate inputs in production. We represent these as $\alpha_{l,ft}^j$ and $\alpha_{m,ft}^j$ respectively. At the firm level, we then calculate the ordinary share of "production" as $s_{ft}^j \equiv \frac{v_{ft}^j - x_{IA,ft}^j - x_{PA,ft}^j}{v_{ft}^j}$ where v_{ft}^j is total output by firm f residing in ISIC industry j in year t, $x_{IA,ft}^j$ is import and assembly exports at the same level, and $x_{PA,ft}^j$ is pure assembly exports at the same level. We take "processing" to be the sum of pure assembly and import and assembly. We then estimate the following equation at the industry-year level

$$\alpha_{l,ft}^j = \beta_t^j + \gamma_t^j s_{ft}^j + \epsilon_{ft}^j$$

where ϵ_{ft}^j has the usual favorable properties. We weight observations by total firm output. In the manufacturing data, firms are nearly always assigned to one industry (unlike the transactions data). This estimation gives us JT estimates of β_t^j and another JT estimates of γ_t^j. We construct $\widehat{\alpha}_{l,ot}^j \equiv \widehat{\beta}_t^j + \widehat{\gamma}_t^j$ and $\widehat{\alpha}_{l,pt}^j \equiv \widehat{\beta}_t^j$ such that our cost shares are what would be expected from a firm engaging in only ordinary ($s_{ft}^j = 1$) or only processing ($s_{ft}^j = 0$) production. Construction of intermediate inputs' share $\sum_k \gamma_o^j$ follows analogously from a similar regression with $\alpha_{m,ft}^j$ on the left hand side. $\widehat{\alpha}_{k,ot}^j$ is then constructed as $1 - \widehat{\alpha}_{l,ot}^j - \widehat{\alpha}_{m,ot}^j$.

Appendix C. Measuring X_{oo}^j and X_{po}^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 5 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. We 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_{no}^j and X_{np}^j, this gives us $3J$ equations and $6J$ unknowns : Y_o^j, Y_p^j, X_{oo}^j, X_{po}^j, X_{op}^j, X_{pp}^j for each j. Because processing firms are not allowed to sell to ordinary firms, X_{op}^j=0. We also assume that processing firms cannot sell to other processing firms such that X_{pp}^j=0. The first is a legal restriction, the second is an identifying assumption.[64] This gives the following system of equations:

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

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

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

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

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

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

The final step in this decomposition starts by using

$$\frac{X_{po}^j}{X_{oo}^j} = \frac{X_p^j / \Phi_p^j}{X_o^j / \Phi_o^j} \tag{A13}$$

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

where

$$\Phi_p^j = \lambda_o^j \left(c_o^j \kappa_{po}^j\right)^{-\theta^j} + \sum_{i'=1}^{N} \lambda_{i'}^j \left(c_{i'}^j \kappa_{pi'}^j\right)^{-\theta^j} \qquad \Phi_o^j = \lambda_o^j \left(c_o^j \kappa_{oo}^j\right)^{-\theta^j} + \sum_{i'=1}^{N} \lambda_{i'}^j \left(c_{i'}^j \kappa_{oi'}^j\right)^{-\theta^j}.$$

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

$$\frac{X_{pW}^j}{X_{oW}^j} = \frac{\sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{pi}^j\right)^{-\theta^j}}{\sum_{i=1}^{N} \lambda_i^j \left(c_i^j \kappa_{oi}^j\right)^{-\theta^j}} \frac{X_p^j / \Phi_p^j}{X_o^j / \Phi_o^j} \tag{A14}$$

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

$$\frac{X_{pW}^j}{X_{oW}^j} = \left[\frac{\sum_{i=1}^{N} (1 + \tau_{ci}^j)^{\theta^j} X_{oi}^j}{\sum_{i=1}^{N} X_{oi}^j}\right] \frac{X_p^j / \Phi_p^j}{X_o^j / \Phi_o^j}. \tag{A15}$$

Combining equations (A16) and (A15), we can obtain

$$\frac{X_{po}^j}{X_{oo}^j} = \frac{X_{pW}^j}{X_{oW}^j} \left[\frac{\sum_{i=1}^{N} (1 + \tau_{ci}^j)^{\theta^j} X_{oi}^j}{\sum_{i=1}^{N} X_{oi}^j}\right]^{-1} \tag{A16}$$

The relative domestic shipments of ordinary production to processing and ordinary firms in China $\frac{X_{po}^j}{X_{oo}^j}$ 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_{ci}^j is imposed. Intuitively, domestic shipments in China should be more skewed towards processing when the market size is larger (the first term) or when lower average tariffs make those industries more 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:

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

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

$$p_{n,00}^{J+1} = \exp[\hat{\beta}_0 + \hat{\beta}_1 \ln GDP_{n,00} + \hat{\beta}_2 \ln GDP_{n,00}^2 + \hat{\beta}_3 \ln GDP_{n,00}^3 + \hat{\beta}_4 \ln GDP_{n,00}^4 + \frac{4}{15}\hat{\beta}_5].$$

Similarly, the price index for 2007 is computed as

$$p_{n,07}^{J+1} = \exp[\hat{\beta}_0 + \hat{\beta}_1 \ln GDP_{n,07} + \hat{\beta}_2 \ln GDP_{n,07}^2 + \hat{\beta}_3 \ln GDP_{n,07}^3 + \hat{\beta}_4 \ln GDP_{n,07}^4 + \frac{11}{15}\hat{\beta}_5].$$

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

$$\frac{\lambda_n^{J+1}}{\lambda_{us}^{J+1}} = \left[\left(\frac{w_n}{w_{us}}\right)^{\tilde{\gamma}_{0,n}^{J+1}} \left(\frac{r_n}{r_{us}}\right)^{\tilde{\gamma}_{1,n}^{J+1}} \Pi_{k=1}^{J+1} \left[\frac{p_n^k}{p_{us}^k}\right]^{\tilde{\gamma}^{k,J+1}} \right]^{\theta^{J+1}} \left[\frac{p_n^{J+1}}{p_{us}^{J+1}}\right]^{-\theta^{J+1}}$$

Appendix E. Measuring $(t_i^j/t_{us}^j)^{-\theta_j}$

Recall that the exporter fixed effects in the gravity regression can be categorized as follows:

$$\delta_i^{j,x} = -\ln\left[\left(t_i^j\right)^{-\theta^j}\right] \qquad i = 1,...,N \tag{A17}$$

$$\delta_o^{j,x} \equiv -\ln\left\{ (t_o^j)^{-\theta^j} \left[1 + \left[\frac{\lambda_p^j}{\lambda_o^j}\left(\frac{c_p^j}{c_o^j}\right)^{-\theta^j}\right]^{\frac{1}{1-\nu}}\right]^{-\nu} \right\} \tag{A18}$$

$$\delta_p^{j,x} \equiv -\ln\left\{ \lambda_p^j (c_p^j)^{-\theta^j} (t_p^j)^{-\theta^j} \left[1 + \left[\frac{\lambda_o^j}{\lambda_p^j}\left(\frac{c_o^j}{c_p^j}\right)^{-\theta^j}\right]^{\frac{1}{1-\nu}}\right]^{-\nu} \right\}. \tag{A19}$$

For non-China countries, we can exponentiate the estimate $\widehat{\delta}_i^{j,x}$ for $i \neq us$ to obtain a value for t_i^j/t_{us}^j conditional on θ^j:

$$exp\left(-\widehat{\delta}_i^j\right) = \left(\frac{t_i^j}{t_{us}^j}\right)^{-\theta^j}. \tag{A20}$$

The estimation is less straightforward for China because of the extra terms that appear in equations (A18) and (A19) that do not appear in (A17). To solve this, we impose the assumption that $t_o^j = t_p^j$ and refer to this common term as t_c^j. With the estimates of $\frac{\lambda_p^j}{\lambda_o^j}\left(\frac{c_p^j}{c_o^j}\right)^{-\theta_j}$ from equation (18) and the estimate of $\widehat{\delta}_o^{j,x}$, we can back out $\left(\frac{t_c^j}{t_{us}^j}\right)^{-\theta^j}$ from equation (A18).

Appendix F. Roundabout Shipping Data Construction

This appendix describes our estimation strategy for the case that processing firms can sell their products to China's market through roundabout trade. More specifically, they can ship their products out of China, and then re-sell the products back to China. If they sell to domestic ordinary firms, they incur both roundabout transportation cost and import tariffs. If they sell to domestic processing firms, they only incur the associated transportation cost.

F.1 Measuring X^j_{oo}, X^j_{po}, and X^j_{op}

If we allow processing firms to sell back to China through round-about trade, π^j_{op} and π^j_{pp} are no longer zero, and they are given by

$$\pi^j_{oo} = \frac{(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{oo}\right)^{-\frac{\theta^j}{1-\nu}}}{(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{oo}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{op}\right)^{-\frac{\theta^j}{1-\nu}}} \times \frac{\left[(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{oo}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{op}\right)^{-\frac{\theta^j}{1-\nu}}\right]^{1-\nu}}{\Phi^j_o}. \tag{A21}$$

$$\pi^j_{po} = \frac{(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{po}\right)^{-\frac{\theta^j}{1-\nu}}}{(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{po}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{pp}\right)^{-\frac{\theta^j}{1-\nu}}} \times \frac{\left[(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{po}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{pp}\right)^{-\frac{\theta^j}{1-\nu}}\right]^{1-\nu}}{\Phi^j_p}. \tag{A22}$$

$$\pi^j_{op} = \frac{(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{op}\right)^{-\frac{\theta^j}{1-\nu}}}{(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{oo}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{op}\right)^{-\frac{\theta^j}{1-\nu}}} \times \frac{\left[(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{oo}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{op}\right)^{-\frac{\theta^j}{1-\nu}}\right]^{1-\nu}}{\Phi^j_o}. \tag{A23}$$

$$\pi^j_{pp} = \frac{(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{pp}\right)^{-\frac{\theta^j}{1-\nu}}}{(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{po}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{pp}\right)^{-\frac{\theta^j}{1-\nu}}} \times \frac{\left[(\lambda^j_o)^{\frac{1}{1-\nu}}\left(c^j_o\kappa^j_{po}\right)^{-\frac{\theta^j}{1-\nu}}+(\lambda^j_p)^{\frac{1}{1-\nu}}\left(c^j_p\kappa^j_{pp}\right)^{-\frac{\theta^j}{1-\nu}}\right]^{1-\nu}}{\Phi^j_p}. \tag{A24}$$

Note that $\kappa^j_{op} = \kappa^j_{pp}(1+\tau^j_{cp})$, where τ^j_{cp} denotes the tariff imposed on processing goods that re-enter China. (The empirical counterpart of τ^j_{cp} is the MFN tariff imposed on good j by China.) κ^j_{pp} captures transportation costs associated with two times the spatial distance between Hong Kong and Shanghai.[65] Similar to our baseline analysis, we assume that $\kappa^j_{oo} = \kappa^j_{po} = 1$. The remaining

[65] We assume that transportation cost incurred by the roundabout trade equals to the shipping cost along the route Shanghai – Hong Kong – Shanghai.

gravity equations are the same as our baseline case. With these relationships, we can derive the following equations.

$$\frac{X^j_{po}}{X^j_{oo}} = \left(\frac{X^j_{oo}+X^j_{op}}{X^j_{po}+X^j_{pp}}\right)^{\frac{\nu}{1-\nu}} \left(\frac{X^j_{pW}}{X^j_{oW}}\right)^{\frac{1}{1-\nu}} \left[\frac{\sum_{i=1}^N (1+\tau^j_{ci})^{\theta^j} X^j_{oi}}{\sum_{i=1}^N X^j_{oi}}\right]^{-\frac{1}{1-\nu}} \tag{A25}$$

$$\frac{X^j_{pp}}{X^j_{op}} = \left(\frac{X^j_{oo}+X^j_{op}}{X^j_{po}+X^j_{pp}}\right)^{\frac{\nu}{1-\nu}} \left(\frac{X^j_{pW}}{X^j_{oW}}\right)^{\frac{1}{1-\nu}} \left[\frac{\sum_{i=1}^N (1+\tau^j_{ci})^{\theta^j} X^j_{oi}}{\sum_{i=1}^N X^j_{oi}}\right]^{-\frac{1}{1-\nu}} \left(1+\tau^j_{cp}\right)^{\frac{\theta^j}{1-\nu}} \tag{A26}$$

To back out X^j_{oo}, X^j_{po}, and X^j_{op}, we use equations (A25) and (A26) and the following identity equations:

$$Y^j_c = Y^j_o + Y^j_p \tag{A27}$$

$$Y^j_o = \sum_{n=1}^N X^j_{no} + X^j_{oo} + X^j_{po} = X^j_{Wo} + X^j_{oo} + X^j_{po} \tag{A28}$$

$$Y^j_p = \sum_{n=1}^N X^j_{np} + X^j_{op} + X^j_{pp} = X^j_{Wp} + X^j_{op} + X^j_{pp} \tag{A29}$$

We calculate X^j_{pp}, i.e., total value shipment of processing sector to itself, from the customs transaction-level data. Together with the information on X^j_{Wo}, X^j_{Wp}, τ^j_{ci}, τ^j_{cp}, and Y^j_c, we can solve for X^j_{oo}, X^j_{po}, X^j_{op}, Y^j_o and Y^j_p from equations (A25)-(A29).

F.2 Measuring λ^j_o, λ^j_p, and t^j_c

We run the gravity equation (20) in the main text. In this case, π^j_{pi}/π^j_{pp} is well-defined, and hence we can simultaneous back out $\hat{\delta}^j_p$ and $\hat{\delta}^{j,x}_p$. More importantly, with round-about trade, the interpretations of the estimated fixed effects for processing and ordinary sectors are different:

$$\widehat{\delta}^j_o = \ln\left(\left[\lambda^j_o\right]^{\frac{1}{1-\nu}} \left[c^j_o\right]^{-\frac{\theta^j}{1-\nu}} \left[\left[\lambda^j_o\right]^{\frac{1}{1-\nu}} \left[c^j_o\right]^{-\frac{\theta^j}{1-\nu}} + \left[\lambda^j_p\right]^{\frac{1}{1-\nu}} \left[c^j_p \kappa^j_{op}\right]^{-\frac{\theta^j}{1-\nu}} \right]^{-\nu} \right) \tag{A30}$$

$$\widehat{\delta}^j_p = \ln\left(\left[\lambda^j_p\right]^{\frac{1}{1-\nu}} \left[c^j_p \kappa^j_{pp}\right]^{-\frac{\theta^j}{1-\nu}} \left[\left[\lambda^j_o\right]^{\frac{1}{1-\nu}} \left[c^j_o\right]^{-\frac{\theta^j}{1-\nu}} + \left[\lambda^j_p\right]^{\frac{1}{1-\nu}} \left[c^j_p \kappa^j_{pp}\right]^{-\frac{\theta^j}{1-\nu}} \right]^{-\nu} \right) \tag{A31}$$

$$\widehat{\delta}^{j,x}_o = -\ln\left(\left[t^j_o\right]^{-\theta^j} \left[\frac{\left[\lambda^j_o\right]^{\frac{1}{1-\nu}} \left[c^j_o\right]^{-\frac{\theta^j}{1-\nu}} + \left[\lambda^j_p\right]^{\frac{1}{1-\nu}} \left[c^j_p\right]^{-\frac{\theta^j}{1-\nu}}}{\left[\lambda^j_o\right]^{\frac{1}{1-\nu}} \left[c^j_o\right]^{-\frac{\theta^j}{1-\nu}} + \left[\lambda^j_p\right]^{\frac{1}{1-\nu}} \left[c^j_p \kappa^j_{op}\right]^{-\frac{\theta^j}{1-\nu}}} \right]^{-\nu} \right) \tag{A32}$$

$$\widehat{\delta}^{j,x}_p = -\ln\left(\left[t^j_p\right]^{-\theta^j} \left[\kappa^j_{pp}\right]^{\frac{\theta^j}{1-\nu}} \left[\frac{\left[\lambda^j_o\right]^{\frac{1}{1-\nu}} \left[c^j_o\right]^{-\frac{\theta^j}{1-\nu}} + \left[\lambda^j_p\right]^{\frac{1}{1-\nu}} \left[c^j_p\right]^{-\frac{\theta^j}{1-\nu}}}{\left[\lambda^j_o\right]^{\frac{1}{1-\nu}} \left[c^j_o\right]^{-\frac{\theta^j}{1-\nu}} + \left[\lambda^j_p\right]^{\frac{1}{1-\nu}} \left[c^j_p \kappa^j_{pp}\right]^{-\frac{\theta^j}{1-\nu}}} \right]^{-\nu} \right) \tag{A33}$$

We can solve for λ_o^j and λ_p^j from equations (A30) and (A31). As in our baseline analysis, we impose the restriction that $t_o^j = t_p^j = t_c^j$. The solution for t_c^j is the minimum distance estimator for equations (A32) and (A33). The calibration for λ_i^j and t_i^j for countries in the ROW remain the same as our baseline analysis.

Appendix G. Solution Algorithm

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 $\tilde{\lambda}_n^j \equiv \frac{\lambda_i^j}{\lambda_{us}^j}$ and κ_{ni} $(i = 1,...,N)$, we can solve the model using the following solution algorithm:

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

- Solve prices P_n^j and variable production costs c_n^j from the following equations:

$$c_n^j \equiv \Upsilon_n^j w_n^{\gamma_{0,n}^j} r_n^{\gamma_{1,n}^j} \Pi_{k=1}^{J+1} [p_n^k]^{\gamma_n^{kj}} \quad \text{for all } n = 1,...,N,o \text{ and } j$$

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

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

For $j = J + 1$,

$$\begin{cases} p_n^{J+1} = \left[\tilde{\lambda}_n^{J+1} \left(c_n^{J+1} \right)^{-\theta^{J+1}} \right]^{-\frac{1}{\theta^{J+1}}} & \forall n \neq o,p \\ p_o^{J+1} = \left[\tilde{\lambda}_o^{J+1} \left(c_o^{J+1} \right)^{-\theta^{J+1}} \right]^{-\frac{1}{\theta^{J+1}}} \\ p_p^{J+1} = +\infty \end{cases}$$

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

$$\begin{cases} \pi_{ni}^j = \frac{\tilde{\lambda}_i^j (c_i^j \kappa_{ni}^j)^{-\theta^j}}{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j \right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\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 \tilde{\lambda}_{i'}^j \left(c_{i'}^j \kappa_{ni'}^j \right)^{-\theta^j}} & \forall n \neq o,p \\ \pi_{no}^j = \frac{(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j \right)^{-\frac{\theta^j}{1-\nu}}}{(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j \right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j \right)^{\frac{-\theta^j}{1-\nu}}} \frac{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j \right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(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(c_o^j \kappa_{no}^j \right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\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 \tilde{\lambda}_{i'}^j \left(c_{i'}^j \kappa_{ni'}^j \right)^{-\theta^j}} \\ \pi_{np}^j = \frac{(\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j \right)^{-\frac{\theta^j}{1-\nu}}}{(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j \right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(c_p^j \kappa_{np}^j \right)^{\frac{-\theta^j}{1-\nu}}} \frac{\left[(\tilde{\lambda}_o^j)^{\frac{1}{1-\nu}} \left(c_o^j \kappa_{no}^j \right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\lambda}_p^j)^{\frac{1}{1-\nu}} \left(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(c_o^j \kappa_{no}^j \right)^{\frac{-\theta^j}{1-\nu}} + (\tilde{\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 \tilde{\lambda}_{i'}^j \left(c_{i'}^j \kappa_{ni'}^j \right)^{-\theta^j}} \end{cases}$$

For $n = o$,

$$\begin{cases} \pi^j_{oi} = \frac{\tilde{\lambda}^j_i (c^j_i \kappa^j_{oi})^{-\theta^j}}{\tilde{\lambda}^j_o \left(c^j_o \kappa^j_{oo}\right)^{-\theta^j} + \sum_{i'=1}^N \tilde{\lambda}^j_{i'} \left(c^j_{i'} \kappa^j_{oi'}\right)^{-\theta^j}} & \forall i \neq o,p \text{ and } j \\ \pi^j_{oo} = \frac{\tilde{\lambda}^j_o (c^j_o \kappa^j_{oo})^{-\theta^j}}{\tilde{\lambda}^j_o \left(c^j_o \kappa^j_{oo}\right)^{-\theta^j} + \sum_{i'=1}^N \tilde{\lambda}^j_{i'} \left(c^j_{i'} \kappa^j_{oi'}\right)^{-\theta^j}} & \forall j \\ \pi^j_{op} = 0 \quad \forall j \end{cases}$$

For $n = p$,

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

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

$$X^j_n = \alpha^j_n \left(w_n L_n + r_n K_n + \sum_{j=1}^{J+1} \sum_{i=1}^{N+2} \tau^j_{ni} X^j_n \frac{\pi^j_{ni}}{1 + \tau^j_{ni}} \right) + \sum_{k=1}^{J+1} \gamma^{jk}_n \sum_{i=1}^{N+2} X^k_i \frac{\pi^k_{in}}{1 + \tau^k_{in}} \quad \forall j$$

For $n = o$,

$$X^j_o = \alpha^j_c \left(w_c L_c + r_c K_c + \sum_{j=1}^{J+1} \sum_{i=1}^{N+1} \tau^j_{oi} X^j_o \frac{\pi^j_{oi}}{1 + \tau^j_{oi}} \right) + \sum_{k=1}^{J+1} \gamma^{jk}_o \sum_{i=1}^{N+2} X^k_i \frac{\pi^k_{io}}{1 + \tau^k_{io}} \quad \forall j$$

For $n = p$,

$$X^j_p = \sum_{k=1}^{J+1} \gamma^{jk}_p \sum_{i=1}^{N} X^k_i \frac{\pi^k_{ip}}{1 + \tau^k_{ip}} \quad \forall j$$

(2) Update $\{w'_n, r'_n\}_{n=1}^{N,c}$ with the labor and capital clearing conditions:

$$\begin{cases} \sum_{j=1}^{J+1} \gamma^j_{0n} \sum_{i=1}^{N+2} X^j_i \frac{\pi^j_{in}}{1+\tau^j_{in}} = w'_n L_n \quad \text{if } n \neq c \\ \sum_{j=1}^{J+1} \gamma^j_{0o} \sum_{i=1}^{N+2} X^j_i \frac{\pi^j_{io}}{1+\tau^j_{io}} + \sum_{j=1}^{J} \gamma^j_{0p} \sum_{i=1}^{N} X^j_i \frac{\pi^j_{ip}}{1+\tau^j_{ip}} = w'_c L_c \quad \text{if } n = c \end{cases}$$

and

$$\begin{cases} \sum_{j=1}^{J+1} \gamma^j_{1n} \sum_{i=1}^{N+2} X^j_i \frac{\pi^j_{in}}{1+\tau^j_{in}} = r'_n K_n \quad \text{if } n \neq c \\ \sum_{j=1}^{J+1} \gamma^j_{1o} \sum_{i=1}^{N+2} X^j_i \frac{\pi^j_{io}}{1+\tau^j_{io}} + \sum_{j=1}^{J} \gamma^j_{1p} \sum_{i=1}^{N} X^j_i \frac{\pi^j_{ip}}{1+\tau^j_{ip}} = r'_c K_c \quad \text{if } n = c \end{cases}$$

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

Appendix H. Additional Results

Table 7: Real Wages and Income: Counterfactual Simulations with Heterogeneous θ^j

Specification Number	**Processing Specification Description**	**Real Wage (rel. to US)** (1)	**Real Factor Income (rel. to US)** (2)	**Real Income (rel. to US)** (3)
(1)	Benchmark	1.000	1.000	1.000
(2)	No exemption	0.999	1.000	1.000
(3)	No exemption, sells domestically	1.056	1.020	1.020
(4)	Sells domestically	1.060	1.020	1.020
(5)	No Processing	0.993	0.995	0.998

Notes: Row (1) represents the baseline equilibrium in which actual values of productivity and tariffs are imposed and processing is not allowed to sell domestically. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do: $\tau^j_{pn} = \tau^j_{on}\ \forall\ j,n$. Row (3) allows processing firms to sell to the ordinary sector and to the processing sector but loses their tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$ and $\tau^j_{pn} = \tau^j_{on}\ \forall\ j,n$. Row (4) is the same as row (3) but processing keeps its tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$. Row (5) imposes infinite trade costs on all shipments out of the processing sector: $\kappa^j_{np} = \infty\ \forall j,n$. Real factor income=wage+capital income. Real income=wage+capital income+tariff revenue. θ^j from Caliendo-Parro (2015) and $\nu = 0.72$.

Table 8: Estimates $\hat{\nu}^j$

ISIC Code	ISIC Description	$\hat{\nu}^j$	Standard Error
15	Food and Beverages	0.765	0.064
17	Textiles	0.274	0.138
18	Wearing Apparel	0.468	0.221
19	Leather Products	0.513	0.075
20	Wood and Wood products, except furniture	0.395	0.121
21	Paper and Paper products	0.219	0.09
22	Publishing	0.588	0.043
24	Chemicals and Chemical Products	0.414	0.055
25	Rubber and Plastic Products	0.758	0.093
26	Non-metallic Mineral Products	1.224	0.17
27	Basic Metals	1.264	0.148
28	Fabricated Metal Products	0.955	0.153
29	Machinery and Equipment n.e.c.	0.636	0.045
30	Office, Accounting, and Computing machinery	1.093	0.056
31	Electrical Machinery and Apparatus n.e.c	1.061	0.04
32	Radio, Television, and Communication equipment	0.889	0.06
33	Medical, Precision, and Optical instruments	0.656	0.035
34	Motor vehicles	0.473	0.07
35	Other transport equipment	0.65	0.053
36	Furniture; manufacturing n.e.c	1.084	0.084
–	Non-Traded	0.72	–

Notes: These estimates of ν^j are based on estimation of equation (13) using two-digit subsamples of the four-digit pooled data described in the text. The first two columns is the ISIC revision 3 two-digit ISIC code and its verbal description. The third column is the point estimate, and the fourth column is the standard errors clustered by country-triads. While the point estimates for industries 26, 27, 30, 31, and 36 do not satisfy the theoretical restriction of $0 \leq \nu < 1$, we cannot reject the null that they are equal to unity at p=0.05. In the counterfactual simulations these values are set equal to 0.99. We set $\nu^{non-traded} = 0.72$.

Table 9: Real Wages and Income: Counterfactual Simulations with Hetreogeneous ν^j

Specification Number	**Processing Specification Description**	**Real Wage (rel. to US)**	**Real Factor Income (rel. to US)**	**Real Income (rel. to US)**
(1)	Benchmark	1.000	1.000	1.000
(2)	No exemption	0.999	1.001	1.001
(3)	No exemption, sells domestically	1.084	1.033	1.033
(4)	Sells domestically	1.087	1.034	1.034
(5)	No Processing	0.982	0.993	0.993

Notes: Row (1) represents the baseline equilibrium in which actual values of productivity and tariffs are imposed and processing is not allowed to sell domestically. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do: $\tau^j_{pn} = \tau^j_{on}\ \forall\ j{,}n$. Row (3) allows processing firms to sell to the ordinary sector and to the processing sector but loses their tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$ and $\tau^j_{pn} = \tau^j_{on}\ \forall\ j{,}n$. Row (4) is the same as row (3) but processing keeps its tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$. Row (5) imposes infinite trade costs on all shipments out of the processing sector: $\kappa^j_{np} = \infty\ \forall j{,}n$. Real factor income=wage+capital income. Real income=wage+capital income+tariff revenue. $\theta^j = 4$ and ν^j calculated for two-digit industries.

Table 10: Real Wages and Income: Counterfactual Simulations with $\nu^j = 0$

Specification Number	**Processing Specification Description**	**Real Wage (rel. to US)**	**Real Factor Income (rel. to US)**	**Real Income (rel. to US)**
(1)	Benchmark	1.000	1.000	1.000
(2)	No exemption	0.999	1.000	1.000
(3)	No exemption, sells domestically	1.130	1.101	1.091
(4)	Sells domestically	1.132	1.103	1.092
(5)	No Processing	0.978	0.987	0.982

Notes: Row (1) represents the baseline equilibrium in which actual values of productivity and tariffs are imposed and processing is not allowed to sell domestically. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do: $\tau^j_{pn} = \tau^j_{on}\ \forall\ j{,}n$. Row (3) allows processing firms to sell to to the ordinary sector and to the processing sector but loses their tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$ and $\tau^j_{pn} = \tau^j_{on}\ \forall\ j{,}n$. Row (4) is the same as row (3) but processing keeps its tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$. Row (5) imposes infinite trade costs on all shipments out of the processing sector: $\kappa^j_{np} = \infty\ \forall j{,}n$. Real factor income=wage+capital income. Real income=wage+capital income+tariff revenue. $\theta^j = 4$ and $\nu^j = 0$.

Table 11: Real Wages and Income: Counterfactual Simulations with Roundabout Shipping

Specification Number	**Processing Specification Description**	**Real Wage (rel. to US)**	**Real Factor Income (rel. to US)**	**Real Income (rel. to US)**
(1)	Benchmark	1.000	1.000	1.000
(2)	No exemption	0.998	1.001	1.001
(3)	No exemption, sells domestically	1.041	1.016	1.010
(4)	Sells domestically	1.045	1.017	1.009
(5)	No Processing	0.984	0.997	0.997

Notes: All specifications correspond to the case of roundabout shipping as described in the text. Row (1) represents the baseline equilibrium in which actual values of productivity and tariffs are imposed and processing is not allowed to sell domestically. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do: $\tau^j_{pn} = \tau^j_{on}\ \forall\ j,n$. Row (3) allows processing firms to sell to the ordinary sector and to the processing sector but loses their tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$ and $\tau^j_{pn} = \tau^j_{on}\ \forall\ j,n$. Row (4) is the same as row (3) but processing keeps its tariff exemption: $\kappa^j_{op} = \kappa^j_{pp} = 1$. Row (5) imposes infinite trade costs on all shipments out of the processing sector: $\kappa^j_{np} = \infty\ \forall j,n$. Real factor income=wage+capital income. Real income=wage+capital income+tariff revenue. $\theta^j = 4$ and $\nu^j = 0.72$.