Is Processing Good?: Theory and Evidence from China *

Loren Brandt[†] Bingjing Li[‡] Peter M. Morrow[§]

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ABSTRACT:

Policies encouraging processing trade are common in developing countries and are thought to encourage integration into global markets. Agents engaged in processing production import intermediate inputs and capital equipment duty free but are not allowed to sell these goods or the resulting output on the domestic market. For ordinary production, the reverse holds: imports are subject to tariffs but domestic sales are allowed. This paper studies the welfare effects of these policies using Chinese data for 109 industries for 2000-2007. Counterfactual policy experiments imply large welfare losses ($\approx 3-7\%$) to Chinese agents from not being allowed to buy processing output on the domestic market. There are smaller welfare effects ($< 1\%$) from the duty free status of processing imports. We also develop a new method to estimate correlation parameters for multivariate Fréchet distributions with trade models that delivers multiplicative gravity equations.

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

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

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

1. Introduction

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 explanations for why productivity might differ between the two organizational forms, largely related to differences in the tasks carried

[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, restrictions on maquiladoras to sell 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).

out and the capabilities required.[2]

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 quantitative implications of China's position in global value chains.

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. 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 sell 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. More explicitly, we assume productivity draws for ordinary and processing within an industry are stochastic but imperfectly correlated using the multivariate Fréchet distribution as in Ramondo and Rodríguez-Clare (2013). This captures our prior that productivity in ordinary and processing production are unlikely the same, but might still be

[2]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. On the other hand, firms involved in ordinary production typically require a much broader set of capabilities that span design, local sourcing, manufacturing, and logistics. These differences in firms' abilities to use high quality inputs, design goods, and manage supply chains as well as the impact of these activities on measured productivity can lead to differences in productivity between ordinary and processing production. Even more simply, higher levels of multinational activity in processing suggest that foreign affiliates may be bringing different states of technology to China.

[3]Madani (1999), OECD (2007) offer descriptive analysis of processing but do not engage in formal cost-benefit analysis. Panagariya (1992) offers an early welfare analysis of duty drawbacks in the context of a small open economy, while Ianchovichina (2007) assesses the welfare effects of tariff drawbacks for China in the context of Panagariya (1992). 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.

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 the idiosyncratic portions of the productivity draws for ordinary and processing production are correlated. 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 between 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.

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.[5]

Third, we find large welfare *gains* in the domestic economy from eliminating the domestic sales' restrictions on the processing production. 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 would crowd out imports.[6] Laborers are better off relative to owners of capital for two reasons: first, processing is generally more labor intensive than ordinary

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

[5]This is based on processing being approximately 10% of sales in our data and manufacturing being approximately 45% of gross aggregate output (Timmer, Dietzenbacher, Los, Stehrer and Vries (2015)).

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

production; and second, the processing sector grows from 12% to 40% of tradable output in the counterfactual.

Eliminating the restriction on domestic sales for processing is potentially more powerful than international trade liberalization due to the presence of large documented barriers to international trade. Because domestic sales face substantially lower barriers, 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.[7] The importance of domestic market liberalization for welfare links this paper to other papers that find large welfare effects of reducing barriers to domestic trade and migration [e.g. Atkin and Donaldson (2015) and Tombe and Zhu (forthcoming)].[8]

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 land, while Brandt, Kambourov and Storesletten (2018) look at barriers to firm entry. In our study of the welfare effects of China's processing regime, this paper is also related to Defever and Riano (2017) who find welfare losses resulting from from export subsidies.[9] Branstetter and Lardy (2008) argue that China's processing regime helped to reduce the distorting effect of tariffs. However, they

[7] 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 in response, offsetting some of the gains from lower domestic mark-ups. Defever and Riano (2017) explore the welfare effect of special tax treatment for processing firms using a two country-single sector model. In the context of a Melitz (2003) model, they argue that special tax treatment afforded to processing firms disincentivized entry by Chinese firms into domestic markets leading to a higher domestic price index.

[8] 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"). 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 to 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 an ordinary draw and a processing draw and chooses a single organizational form at the firm level.

[9] Their analysis is in the context of a one sector model that does not distinguish between processing and ordinary exports.

do not consider the costs of the restrictions on domestic sales as we do here.

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 productivity differences and the results of the counterfactual simulations. Section 7 concludes.

2. Context/Institutions

We now briefly review select institutional details of China's processing regime that are pertinent to this paper.[10] 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 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.[11]

In the aggregate, the share of processing increased between 1990 and 2000 and then began to fall. In 1999, processing exports represented 57.3% of China's total exports, but by 2006 this fell to 53.6% and in 2012 were only 34.8%.[12] 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. 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 from 17.3% in 2000 to 9.1% in 2007.

[10]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 longer and more detailed discussions of these dual trade forms, see discussions in Feenstra and Hanson (2005), Branstetter and Lardy (2008), Fernandes and Tang (2012).

[11]In addition to establishing a close proximity to Hong Kong and Taiwan, the south-east placement of early special economic zones further insulated industry in Beijing and Shanghai from any competition.

[12]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 here. 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, slightly less productive that ordinary and also experienced slightly slower productivity growth than ordinary between 2000 and 2006.[13] Taken at face value, this would suggest minimal gains. However, this literature usually ignores *across-industry* heterogeneity in this difference which can generate gains when processing has a comparative advantage in some goods and industries. In addition, if there productivity differences across varieties within an industry, this can generate *within-industry* gains from comparative advantage.[14] We discuss these differences in detail in section 6.2.

3. Model

Our quantitative model possesses several important features. First, in order to conduct quantitative experiments, 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 concentrated in certain industries [e.g. Brandt and Morrow (2017)]. 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 as follows: 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 but the reverse is not allowed. In what follows, we refer to whether sales or exports go through ordinary or processing as the "organization

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

[14] This heterogeneity is measured by the parameter θ in models based on Eaton and Kortum (2002) and is isomorphic to the elasticity of substitution in models based on Krugman (1980).

of production" or the "organization of trade", respectively. We further assume that this distinction holds only for China: all countries outside China engage in ordinary trade exclusively.[15]

3.1 Preliminaries

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

Each country possesses exogenous endowments of 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. We can then write their factor returns as w_c and r_c.[16]

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

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

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

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 $\gamma_{l,n}^j + \gamma_{k,n}^j + \sum_{k=1}^{J}\gamma_n^{kj} = 1$. $l_n^j(\omega^j)$ 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 to vary across both industries and countries within an industry. Unit cost is $c_n^j/z_n^j(\omega^j)$ where the cost of an input bundle is

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

and Υ_n^j is an industry-country specific constant.[17] p_n^k is the price of a composite unit of k in country n which we discuss shortly.

As in Caliendo and Parro (2015), the composite intermediate in sector j, Q_n^j, is a CES aggregate of industry-specific varieties such that $Q_n^j = \left[\int x_n^j(\omega^j)^{\frac{\sigma^j-1}{\sigma^j}}d\omega^j\right]^{\frac{\sigma^j}{\sigma^j-1}}$ where $x_n^j(\omega^j)$ is the demand for intermediate goods ω^j from the lowest cost supplier. This composite is used for intermediate inputs for downstream production as well as final goods in consumption. 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.[18] For processing, $Q_p^j = \sum_{k=1}^{J}\int m_p^{jk}(\omega^k)d\omega^k$ as all of the composite processing output must be used in the production of processing goods and none can be used to satisfy final demand.

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

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

3.4 *Pricing and Transport Costs*

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. Transport costs and tariffs imply that even if a given source country is the lowest cost provider of a given variety in some destination market, it need not be the lowest cost supplier to all destinations.

There are two components of trade costs: iceberg international trade costs and ad-valorem tariffs. Treating the former first, define d_{ni} as the distance between n and i, and $g^j(d_{ni})$ as a weakly increasing industry-specific function that maps distance into iceberg trade costs. We assume that the function $g^j(d_{ni})$ is symmetric in distance such that $g^j(d_{ni}) = g^j(d_{in})$. To allow for asymmetries, as in Waugh (2010), exporter i-industry j specific multiplicative iceberg costs t_i^j allow total iceberg costs between two locations to depend on the direction in which the shipment is going. Define τ_{ni}^j to be the the statutory ad-valorem tariff that n imposes on varieties of good j shipped from i. All exports from China to external markets are subject to the same tariff level regardless of their organization such that $\tau_{io}^j = \tau_{ip}^j$. Combining these, the total iceberg 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 $\left(\lambda_i^j\right)^{\frac{1}{\theta^j}}$.

However, for ordinary and processing trade within a Chinese industry, this is unsatisfying. First, one one extreme, there is no reason to assume that draws between the two organizational forms are independent as they would if they each had their own Frechét distribution. At the other extreme, it is restrictive to assume that their draws come form the same distribution with a single location parameter. For this reason, we follow Ramondo and Rodríguez-Clare (2013) by assuming correlated draws $\{z_o^j(\omega^j), z_p^j(\omega^j)\}$ for ordinary and processing production from a multivariate Fréchet distibution:

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

where $\nu \in [0,1)$ governs the correlation between z_o and z_p. A higher value of ν increases this correlation, and $\nu = 0$ corresponds to the case where z_o and z_p are independent. Section 5 shows how we can identify ν using a triad approach that builds on Berry (1994) and Caliendo and Parro (2015). As this correlation declines ($\nu \to 0$), heterogeneity in productivity across ordinary and processing increases, leading to larger potential gains from buying from both forms of production relative to buying from only one. As the correlation increases ($\nu \to 1$), the draws are more correlated and there are smaller gains from buying from both forms of production instead of only one.

3.6 *Equilibrium Trade Shares*

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

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

where

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

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

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

See Appendix A.Appendix A for a proof. The first fraction to the right of the equality captures the share of ordinary trade in total *Chinese* exports to destination market n. The second fraction to the right of the equality captures the share of country n expenditures that accrue to China as a whole. The first fraction is larger when λ_o^j/λ_p^j is relatively larger, the relative cost of ordinary trade c_o^j/c_p^j is lower, or iceberg costs confer an advantage to ordinary trade $\kappa_{no}^j < \kappa_{np}^j$.[19] Similarly, the expenditure share accruing to processing is

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

Deriving import shares *into* the processing and ordinary sectors in China is straight-forward and obtained by setting $\kappa_{op}^j = \kappa_{pp}^j = \infty \ \forall \ j$. $\kappa_{op}^j = \infty$ imposes the restriction that processing cannot sell to those organized into ordinary production, and $\kappa_{pp}^j = \infty$ imposes the condition that processing cannot sell to itself.[20] This allows us to derive a share of expenditure by processing accruing to country i as $\pi_{pi}^j = \frac{\lambda_i^j (c_i^j \kappa_{pi}^j)^{-\theta^j}}{\Phi_p^j}$ where Φ_p^j is given by setting $n = p$ and $\kappa_{pp} = \infty$ in equation (5). The

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

[20]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 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%.

share of expenditures in destination o accruing to source i is given analogously: $\pi_{oi}^j = \frac{\lambda_i^j (c_i^j \kappa_{oi}^j)^{-\theta^j}}{\Phi_o^j}$ where Φ_o^j is given by setting $n = o$ and $\kappa_{op}^j = \infty$ in equation (5). See Appendix Appendix A for proofs.[21] 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.

3.7 *Goods Market Clearing*

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

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

It is useful to describe the components of equation (9) in detail. The first component ($\alpha^j I_n$) reflects final consumption expenditure on the industry j composite good in n. For a given industry k-country i pair, the second component, $\gamma_n^{jk} X_i^k \frac{\pi_{in}^k}{1+\tau_{in}^k}$, 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 across i gives global expenditure in industry k accruing to intermediate inputs in industry j, country n; then summing over downstream industries k captures total demand for inputs from industry j that are produced in n.

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

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

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:

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

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

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 $M_{ni}^{j} = X_n^j \frac{\pi_{ni}^{j}}{1+\tau_{ni}^{j}}$ since processing imports are duty free.

3.8 Balanced Trade and Factor market clearing

We impose that income equals expenditure such that all income for a country equals total world expenditure by that country. 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 Appendix A

3.9 Equilibrium

Definition 1 *Given* L_n, K_n, λ_n^j, $g^j(d_{ni})$, τ_{in}^j, α_n^j, γ_n^{jk}, $\gamma_{l,n}^j$, $\gamma_{k,n}^j$, ν, *and* θ^j, *an equilibrium under tariff structure* $\{\tau_{ni}^j\}$ *is a wage vector* $\mathbf{w} \in \mathbf{R}_{++}^{\mathbf{N+1}}$, *a rental rate vector* $\mathbf{r} \in \mathbf{R}_{++}^{\mathbf{N+1}}$, *and prices* $\{p_n^j\}_{j=1,n=1}^{J,N+2}$ *that satisfy equations* (1),(4)-(11), *balanced trade, and factor market clearing for all* j,i.

4. Data

The Data Appendix discusses our data set in detail, but we briefly discuss aspects of it here. Based on data availability, our data cover 24 developed and developing countries for the years 2000-2007, 109 manufacturing sectors, and one non-traded sector. Using as broad coverage of industries as possible is important given the concentration of processing in a small number of industries [see Brandt and Morrow (2017)]. Manufacturing industries are at the four-digit ISIC level and the non-traded sector is a composite of services and agriculture. Aside from China, trade data come from the BACI data base maintained by CEPII.[22] For Chinese exports and imports, transactions data from the Customs Administration of China allow us to distinguish ordinary and processing

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

shipments. To calculate country-industry-level domestic sales, 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.[23] We subtract exports from the Customs Administration to obtain domestic sales.[24] 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 (real) capital stock both come from the Penn World Tables 9.0. INDSTAT provides data for national wages.[25]

The cost share of labor $\gamma^j_{l,n}$ is the share of total output paid to labor in the UN INDSTAT data set for manufacturing and WIOD for the non-traded sector. The share of intermediate inputs is given by one minus the total share of value added in output from the same sources. We assume that capital's share of output, $\gamma^j_{k,n}$, is one minus labor's share minus the share of intermediate inputs. For China, these statistics are derived from the Annual Survey of Manufacturers.[26] We calculate γ^{jk}_n by starting with the world input-output matrix as pubished by Timmer et al. (2015). At the NACE level, this gives us shares of intermediate inputs accruing to input industries. We denote these as $\tilde{\gamma}^{j'k'}$ where $'$ denotes a NACE sector. Using a concordance available from WITS and a proportionality assumption, we create ISIC specific intermediate input shares, $\tilde{\gamma}^{jk}$. We then multiply these by one minus the value added share to create γ^{jk}_n. The Data Appendix describes this in detail.

[23]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 which is why we use the NBS production data. SCALING ISSUES

[24]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 comes from a survey and the transactions data are universal, we scale up the NBS data by using factors derived by comparing output in the NBS data in 2004 with manufacturing census data in the same year.

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

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

5. Mapping Theory onto Empirics

5.1 *Estimates of* θ^j *and* ν.

As in Simonovska and Waugh (2014), we use $\theta^j = 4 \ \ \forall j$.[27] We examine the robustness of our results to alternate values of θ^j in section 6. Because estimates for ν do not exist, we propose a new strategy to estimate its value. We start by taking a stand on the correlation structure of productivity draws. First, as in much of the literature, we assume that productivity draws across countries in a given industry are independent.[28] However, we allow for productivity draws across ordinary and processing production within an industry to be correlated. Using the triad strategy of Caliendo and Parro (2015) in conjunction with equation (6), we 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 share of exports accruing to ordinary exports $s^j_{no} \equiv \frac{\pi^j_{no}}{\pi^j_{no}+\pi^j_{np}}$. When $\nu = 0$, this nests the strategy that Caliendo and Parro (2015). Conditional on θ^j, we can use a simple method of moments strategy to estimate ν.[29] This procedure is valid when all tariffs are set at most favored nation (MFN) rates in which case equation (12) becomes $\left(\frac{\pi^j_{no}\pi^j_{oh}\pi^j_{hn}}{\pi^j_{nh}\pi^j_{ho}\pi^j_{on}}\right) = \left(\frac{s^j_{no}}{s^j_{ho}}\right)^{\nu}$.

ν parameterizes how correlated Chinese productivity draws are across ordinary and processing production. Using the language of discrete choice models [e.g. Berry (1994)], ordinary and processing trade reside within a group. As the parameter ν goes to one, the correlation of productivity

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

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

[29] Unlike Caliendo and Parro (2015), we move the term involving θ^j over to the left hand side. 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 mean that tariff cuts can not matter but it does mean 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.

draws across ordinary and processing within this group goes to one, and as ν approaches zero, the within-group correlation goes to zero.[30] A higher value of ν reduces heterogeneity and leads to a stronger relationship between the within-group share on the right hand side and ordinary market shares on the left hand side. This is analogous to techniques developed in Berry (1994) in which *across-group* market shares are regressed on *within-group* shares to identify within-nest elasticities of substitution in nested-logit models.[31] To our knowledge, this is the first time such a strategy has been used to estimate the 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 estimate the following polled equation:

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

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 normally distributed. The resulting estimate of ν, $\widehat{\nu}$, is 0.72 with a standard error of 0.02 with standard errors clustered by noh triplets. The tight estimate allows us to reject both the null hypotheses that $\nu = 0$ and $\nu = 1$ at conventional levels.[34]

[30]This does not mean that the states of technology λ^j_o and λ^j_p are the same, only that the idiosyncratic variance between the two goes to zero.

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

[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]Although pair specific terms are differenced out, pair-*direction*-specific terms such as tariffs 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 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.

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 both within and across industries affect the 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 akin to classic productivity-based comparative advantage and our counterfactual has the intuitive interpretation as measuring Ricardian gains from domestic market liberalization. Second, when examining the contribution of productivity growth in explaining the increase of ordinary exports vis-a-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.[35] β_d^j is the industry-year-specific

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

effect of being in interval d. b^j_{ni} is the industry-specific effect of sharing a border. When $i \neq o,p$, then $\delta^{j,x}_i \equiv \ln(t^j_i)$. For $i = o$ and $i = p$, respectively,

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

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

The extra terms for China reflect the correlated Fréchet draws.[36] Since π^j_{pp}=0, equation (15) is undefined when processing is the destination location, and shipments for processing only show up as exports. Consequently, any industry-specific fixed effect for processing only identifies the combination of unit cost and the industry-specific exporting cost.

Moving observed tariffs to the left hand side of (14) delivers the following gravity regression where δ^j_i is a country fixed effect within a given industry-level regression:[37]

$$\ln\left(\frac{\pi^j_{ni}}{\pi^j_{nn}}\right) + \theta^j ln(1 + \tau^j_{ni}) = \delta^j_i - \delta^j_n + \sum_{d=1}^{6}\beta^j_d d_{ni,d} + b^j_{ni} + \delta^{j,x}_i + \epsilon^j_{ni} \tag{15}$$

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

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

$$\exp\left(\frac{\widehat{\delta}^j_i}{\widehat{\delta}^j_{us}}\right) = \frac{\lambda^j_i}{\lambda^j_{us}}\left(\frac{c^j_i}{c^j_{us}}\right)^{-\theta^j}. \tag{16}$$

At this point, it is typical to assume common factor cost shares across countries within an industry, such that c^j_i / c^j_{us} is a function of relative input prices and industry-specific common Cobb-Douglas factor shares across countries α^j_l, α^j_k.[38] This allows recovery of estimates of $\lambda^j_i / \lambda^j_{us}$.

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

[37]We do this because of concerns about the endogeneity of tariffs and 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.

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

However, there is no reason to believe that this restriction holds in the data and, for this reason, we follow Caves, Christensen and Diewert (1982) and allow for more general production functions that are well-approximated by the translog function. This allows us to write (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.[39] 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 counterfactuals 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 $\frac{p_n^k}{p_{us}^k}$ to obtain empirical counterparts of $\frac{\lambda_i^j}{\lambda_{us}^j}$ which we obtain following Shikher (2012) and Levchenko and Zhang (2016).[40]

[39]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.

[40]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 δ_o^j, $\delta_o^{x,j}$ and $\delta_p^{j,x}$, we can 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 in 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 relative price index for processing relative to ordinary:

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

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 that ordinary imports are subject to but processing imports are not.

6. Results

In this section, we first briefly discuss the gravity models that we estimate. We then discuss our estimates of total factor productivity for both China's processing and ordinary regimes. We then close by presenting the results of our counterfactual exercises.

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 .961 and .968, respectively.[41] 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*

We now examine ordinary and processing productivity across manufacturing industries in China in 2000 and 2007. Multiple papers have examined relative productivity levels of ordinary and processing firms including Yu (2015), Manova and Yu (2016), Dai et al. (2016), and Li, Smeets and Warzynski (2017) with mixed results.[42] These mixed results may be due to methodological hurdles that make comparison of TFP difficult across the two regimes. Output prices may vary across ordinary and processing within an industry making use of a common deflator problematic.[43] On the input side, using a common intermediate input price deflator is problematic as the differing tariff treatment across these two forms will cause the intermediate input price deflator to be relatively overstated for processing. While more restrictive in some dimensions (e.g. market structure), our approach 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.[44]

Table 1 displays 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 while productivity in processing was only slightly lower. Within industries (row 3), processing was approximately 5%

[41]The minimum is .875 and the maximum is .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 border dummy is positive for 105 out of 109 industries.

[42]Yu (2015) and Manova and Yu (2016) each find evidence that suggests that processing exporters are less productive than ordinary exporters within an industry while Li et al. (2017), using detailed data on physical quantities, finds the opposite using detailed data for one industry. Each finds that processing is less productive on average but do not examine heterogeneity across industries which may be a source of comparative advantage.

[43]See Li et al. (2017).

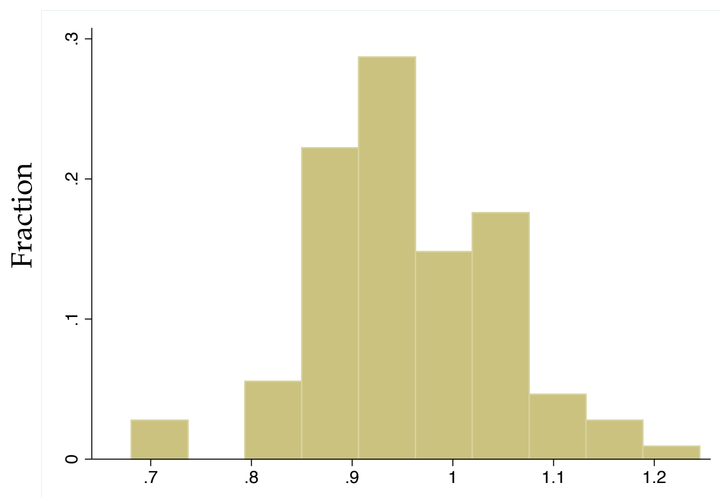
[44]See equation (19).

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 $(\widehat{\lambda}^j_{o,t})^{\frac{1}{\theta}}$ and $(\widehat{\lambda}^j_{p,t})^{\frac{1}{\theta}}$. 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 $TFP^j_{p,2000}/TFP^j_{o,2000}$



$TFP^j_{p,2000}/TFP^j_{o,2000}$

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 $(\widehat{\lambda}^{j}_{o,t})^{\frac{1}{\theta}}$ and $(\widehat{\lambda}^{j}_{p,t})^{\frac{1}{\theta}}$. 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. 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.[45] This finding that processing is slightly less productive on average replicates previous findings (e.g. Yu (2015) and Dai et al. (2016)). However, our finding of substantial heterogeneity is new and suggests possible gains from allowing processing firms to sell domestically due to across-industry comparative advantage. Looking at the bottom three rows, while productivity vis-à-vis the U.S. grew for each type of production, within-sector productivity differences were unchanged on average.

When 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%. But by 2007, there was substantial convergence such that orinary's mean productivity was now 60% of the US while TFP processing only increased to 69%. This change could have been due to either convergence in ordinary's largest sectors or because the sectors in which relative TFP

[45] 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 three sectors for which it is the highest are Office and Computing Machinery (3000), Bodies for Motor Vehicles (3420) , Steam Generators (2813), 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.

for ordinary was highest initially 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).[46]

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.[47] 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.[48] Because of our interest in ordinary relative to processing trade, we also examine the model implied share of aggregate exports accruing to ordinary trade. In the data in 2000, this share was 60% while the model delivers 59%. This is reassuring given that this moment is a not directly targeted in our estimation.[49]

[46]This compares with aggregate TFP growth of 5.1% as measured by the Penn World Tables. This is consistent with low measured TFP growth in services during this period.

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

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

[49]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.

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: $\tau^j_{np} = \tau^j_{no}\ \forall\ j,n$. 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 $\tau^j_{np} = \tau^j_{no}\ \forall\ j,n$. 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 equals wage+capital income+tariff revenue. $\theta^j = 4$ and $\nu = 0.72$.

Processing is not a single policy lever: it combines several policies each of which has potentially different welfare effects. For this reason, our counterfactuals examine the effect of each 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 is not allowed to sell domestically. For ease in interpreting counterfactual welfare effects in the rows that follow, we normalize each 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 lost its duty exemption).[50] 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 a full duty drawback for exports is ambiguous when there are tariffs elsewhere in the economy. Looking at columns (1)-(3), real wages fall slightly although real factor income and real total income are

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

essentially unchanged.[51] These small changes reflect the fact that processing exports as a share of gross manufacturing output by Chinese firms in the data is quite small ($\approx 10\%$ in 2000) and their share of aggregate gross output is even smaller ($\approx 5\%$), and is consistent with relatively the small effects of incremental trade liberalization found in Eaton and Kortum (2002).

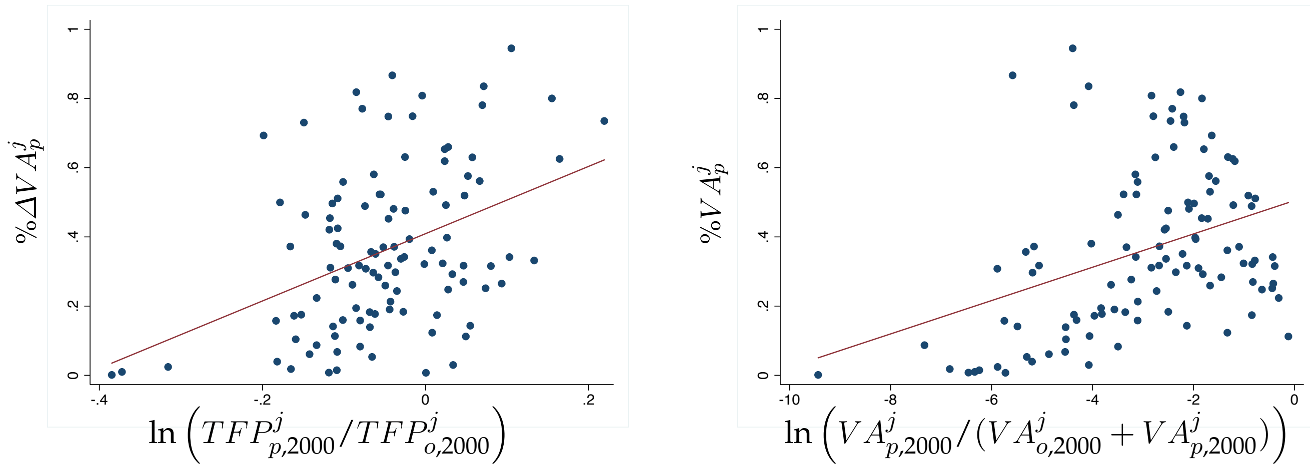
Our second counterfactual experiment focuses on the other major policy component of processing: the restriction from selling to domestic agents. Row 3 of table 4 presents our results for the counterfactual in which processing producers can sell to domestic consumers but lose their tariff exemption. Specifically, we impose $\kappa^j_{pp} = \kappa^j_{op} = 1$ and $\tau^j_{pn} = \tau^j_{on}\ \forall\ n,j$. 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, a counterfactual world in which Chinese consumers can buy from processing producers but processing loses its tariff exemption displays real wages that are 6.9% higher. The reason that these effects is so large is that, *because of transportation costs*, consumers spend a much larger share of their incomes on domestically provided goods than imported goods. Consequently, any policy that affects the menu of prices presented by domestic producers will have a much larger effect than a policy that affects the price charged on imports. The second column shows that real factor income grows by less (3.3%). This is because, within industries, processing production is approximately 4 percentage points more labor intensive than ordinary production. In addition, in this counterfactual, processing grows from 13% to 45% of gross manufacturing output. These two facts imply a large increase in aggregate demand for labor

[51] Real factor income and real total income actually increase slightly with increases of 0.01% for the earlier and 0.03% for the latter.

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

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 (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.

relative to capital.[53] Consequently, our counterfactual has important distributional implications for workers relative to owners of capital. Finally, real total income grows by slight less than total factor income. This is because increased domestic sales by processing crowds out imports, and tariff revenue falls despite the fact that processing is not given a duty drawback in this counterfactual.

Figure 2 illustrates partially the mechanism behind these results. For the panel on the left, the horizontal axis measures $TFP^j_{p,2000}/TFP^j_{o,2000}$ while the vertical axis plots the change in industry value added accruing to processing between the counterfactual in row (3) and the baseline in row (1). Each dot represents an industry. The fact that all points are above the origin shows that processing expands in *all* industries as processing can now access the domestic market. The strong upward sloping relationship suggests that the prohibition from selling domestically is keeping highly productive processing industries smaller than is efficient, and that removing this prohibition

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

allows the most productive segments of processing to grow by the most.[54] The panel on the right plots the same change in industry value added share accruing to processing on the vertical axis but against processing's value added share in 2000 on the horizontal axis. The upward sloping relationship corroborates the panel on the left and shows that industries in which processing was more important in 2000 also grew more across counterfactuals.

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 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 $\kappa_{ip}^{j} = \infty \; \forall i, j$. 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.[55]

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^j. Third, we recalculate the welfare effects of processing when $\nu = 0$ such that the draws between ordinary and processing are independent while still allowing the location parameters λ_o and λ_p to vary. This last counterfactual offers guidance as to what is the size of the bias that might be introduced by assuming uncorrelated productivity draws as opposed to explicitly modelling them using a multi-variate Fréchet distribution. We discuss the results below but relegate all tables to the Appendix.

[54]The industries which contribute most the increase in the aggregate share of processing are intuitive. The following four sectors contribute nearly 25% of the overall change: wearing apparel, plastics products, furniture, Printing, and the manufacture of corrugated paper and paperboard and of containers of paper and paperboard.

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

We start by replicating our results from Table 4 but imposing the values of θ^j estimated in Caliendo and Parro (2015).[56] 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.[57] These alternate 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. This is done by estimating equation (13) for at the two-digit ISIC level as in Caliendo and Parro (2015). Table 8 presents estimates $\hat{\nu}^j$ across 20 industries. We reject the null of zero for all of them. For four, the point estimate is greater than one but we cannot reject that they are less than $\nu^j < 1$ at p=0.05. Table 9 presents our counterfactual simulations following the same format as Table 4. Again, our welfare effects change little although now they are slightly larger than in the primary specifications. Real wages, real factor income, and real total income increase by 8.7%, 3.4%, and 3.4% when processing is allowed to sell domestically but loses its duty drawback.

We next examine how important is our use of 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. Table 10 presents these results. Importantly, we find that assuming that Fréchet draws are uncorrelated between ordinary and processing leads us to overestimate of the welfare gains from allowing processing to sell domestically by between 80% and 230%. This suggests that more careful consideration 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

[56]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.

[57]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.

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.[58] Appendix F describes how data are constructed in this case and presents analogous counterfactuals. As one might suspect, if roundabout shipping is an option the welfare gains are smaller but remain positive (1-4%), much larger than the welfare effects of the duty-drawbacks, and still exhibit the same distributional effects as in the primary results.

6.4 *Counterfacuals: The Organization of Trade*

In a second and distinct set of counterfactuals, we assess the ability of the model to reproduce changes in the share of aggregate exports that are organized through 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. While valuable contributions, both 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 through a set of well-defined quantitative experiments. The counterfactuals in this sub-section fill two holes in this literature: first, we examine the aggregate effect of falling input tariffs on the evolution of ordinary and processing trade in China, an effect that is not identified in reduced form econometric work. Second, by exploiting our productivity measures derived in section 6.2,

[58]For the vast majority of these shipments, the transfer country is listed as being Hong Kong or Taiwan.

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

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
$\frac{\sum_{j,i} X_{ip}^{j}}{\sum_{j,i} X_{ip}^{j}+X_{io}^{j}}$	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.

we examine the effect of changing productivity levels in China which altered relative incentives to source domestically.

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, if $\widehat{\tau}_{oi,2007}^{j} = \tau_{oi,2007}^{j}$, Chinese tariffs to their 2007 level and, if $\widehat{\tau}_{oi,2007}^{j} = \tau_{oi,2000}^{j}$, tariffs are 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.

Row 1 holds tariffs and productivity constant at their 2000 level. The predicted aggregate share of exports organized through ordinary trade (0.593) is very close to the actual number (0.609). Row 2 uses actual changes in tariffs in China 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 ordinary trade. Consistent with this idea, our model implies that approximately 26% of the total change in ordinary exports (2.7 percentage points) can be explained by lower tariffs

[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.

[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.

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

Specification	$\widehat{\tau}^j_{oi,2007}$	$\widehat{\lambda}^j_{o,2007}$	$\widehat{\lambda}^j_{p,2007}$	$\frac{\sum_{j,i}\widehat{X}^j_{ip,2007}}{\sum_{j,i}\widehat{X}^j_{ip,2007}+\widehat{X}^j_{io,2007}}$
(1)	$\tau^j_{oi,2000}$	$\lambda^j_{o,2000}$	$\lambda^j_{p,2000}$	0.593
(2)	$\tau^j_{oi,2007}$	$\lambda^j_{o,2000}$	$\lambda^j_{p,2000}$	0.566
(3)	$\tau^j_{oi,2000}$	$\lambda^j_{o,2007}$	$\lambda^j_{p,2007}$	0.527
(4)	$\tau^j_{oi,2007}$	$\lambda^j_{o,2007}$	$\lambda^j_{p,2007}$	0.507

Notes: This table presents our counterfactual simulations as discussed in section 6.3. The first column states the level that tariffs take in 2007 in China in the simulation. The second column states the ordinary state of technology takes its 2007 level in China in the simulation. The third column states the level that the state of technology for processing takes its 2007 level in China in the simulation. The fourth column displays the model generated share of aggregate exports that are organized through processing trade. See table 5 for actual shares of aggregate trade organized through processing for the countries in the sample. Specification 1 presents model generated data using actual tariffs and states of technology. Specification 2 changes tariffs to their 2007 level. Specification 3 changes states of technology to their 2007 levels. Specification 4 changes both tariffs and states of technology to their 2007 levels.

in China.[61]

The third row keeps tariffs constant but feeds in the observed change in productivity keeping tariffs at their 2000 level. The differential change in ordinary productivity relative to processing trade can explain approximately 64% (6.6 percentage points) of the observed change. As Chinese capabilities increase, ordinary production benefits more heavily 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 all external markets. 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 levels of productivity growth are consistent with the observed change.

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. Similarly, increasing productivity in ordinary production relative to processing, and increasing productivity overall explain approximately 64% of the total change.

[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.

Combined these two effects are consistent with the entirety of the change.[62] [63]

7. Conclusion

Export processing zones and processing activities in general have figured prominently in the strategies of many export-oriented developing countries. Despite much debate as to their effectiveness, simple cost-benefit analyses have been 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 assessed the quantitative importance of two common characteristics of processing regimes: export processing producers are able to import intermediate inputs duty free but are unable to sell their output on the domestic market.

We emphasize three results from our analysis. First, for China in the years considered, productivity differs between ordinary and processing production suggesting that agents engaging in processing are not simply replicating ordinary production, and that there are possible gains from allowing Chinese agents to access processing output. Second, the welfare effects 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). However, third, there are large welfare gains associated with allowing Chinese producers who are engaged in processing to sell domestically. This result is closely linked to the fact that productivity differs across ordinary and processing and this domestic market liberalization would allow for a new form of gains from trade.

Processing is often through to entail benefits such as foreign exchange accumulation and learning-by-doing. These do not show up in our model and their quantitative importance must

[62]Note that because 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 some evidence that domestic market size can affect the organization of trade.

[63]The sum of the counterfactuals changing tariffs *or* productivity levels does not sum to the effect of changing both due to general equilibrium effects and, therefore, these two numbers should not be considered a decomposition.

be large to justify the current processing regime. However, this begins up another question related to optimal policy: is there another set of policies that can encourage this foreign exchange and knowledge accumulation that does not entail the costly distortions that come from processing producers not being allowed to sell domestically?

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Appendix A. Proofs

A.1 Price Distributions

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

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

Using the properties of the 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 product lines in China. The distribution of prices in the Chinese ordinary processing sector is given by

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

where

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

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

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

where

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

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 $\pi_{ni}^j \equiv Pr\left[p_{ni}^j(\omega^j) \le \min\left\{p_{ns}^j(\omega^j); s \neq i\right\}\right] = \int_0^\infty \prod_{s\neq i}\left[1 - G_{ns}^j(p)\right] dG_{ni}^j(p)$. 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, in ordinary sector, the share of expenditure on goods accruing to country i can be derived using the expression above and $\kappa_{op}^j = \infty$:

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

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

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

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

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

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

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

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

$$= \frac{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}}} - \frac{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}}} \int_0^\infty \theta^j \lambda_{w_n}^j exp\Big[-[(\lambda_o^{j\,\frac{1}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}})^{1-\nu} + \lambda_{w_n}^j] w_n^{j\,-\theta^j}\Big] w_n^{j\,-\theta^j-1} dw_n^j$$

$$= \frac{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}}} - \frac{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}}} \frac{\lambda_{w_n}^j}{(\lambda_o^{j\,\frac{1}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}} \mu_n^{j\,-\frac{\theta^j}{1-\nu}})^{1-\nu} + \lambda_{w_n}^j}$$

$$= \frac{\lambda_o^{j\,\frac{1}{1-\nu}}}{\lambda_o^{j\,\frac{1}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}} \mu_n^{j\,\frac{\theta^j}{1-\nu}}} \frac{(\lambda_o^{j\,\frac{1}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}} \mu_n^{j\,\frac{\theta^j}{1-\nu}})^{1-\nu}}{(\lambda_o^{j\,\frac{1}{1-\nu}} + \lambda_p^{j\,\frac{1}{1-\nu}} \mu_n^{j\,\frac{\theta^j}{1-\nu}})^{1-\nu} + \lambda_{w_n}^j}$$

where the second equality follows from the distribution function (A6). Substitute in $\mu_n^j = \frac{c_o^j \kappa_{no}^j}{c_p^j \kappa_{np}^j}$ and $\lambda_{wn}^j = (c_o^j \kappa_{no}^j)^{\theta^j} \sum_{i \neq o,p} \lambda_i^j (c_i^j \kappa_{ni}^j)^{-\theta^j}$ into the last equality, π_{no}^j can be rewritten as

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

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

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

A.3 Market Clearing

Because income equals expenditure:

$$\sum_{j=1}^{J+1} \sum_{i=1}^{N+2} X_n^j \frac{\pi_{ni}^j}{1+\tau_{ni}^j} = \sum_{j=1}^{J+1} \sum_{i=1}^{N+2} X_i^j \frac{\pi_{in}^j}{1+\tau_{in}^j}. \tag{A8}$$

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 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 is available through UN Comtrade (via BACI) and is also available at the HS six-digit level for the same time period. As we discuss below, we aggregate this up to the four-digit ISIC level using a crosswalk.[64]

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

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

The UN INDSTAT data base contains data on output, value added, and total wages at the 4-digit ISIC level of aggregation and is our source for $\gamma^j_{0,n}$ and $\gamma^j_{1,n}$. Data on total labor and capital endowments come from the Penn World Tables 9.0. Next, we require empirical counterparts for $\gamma^{k,j}_n$, the Cobb-Douglas share of product k used in production of j in country n. Next we need input-output Cobb-Douglas shares for the countries in our data set. For this We rely on two data sets. First is the WIOD dataset which–after dropping agriculture, mining, petroleum, and services–allows us to construct a 13 by 13 IO matrix at the NACE level which roughly corresponds to the 2-digit ISIC (revision 3) level. Second we use output from the Industrial Demand-Supply Balance (IDSB) Database at the four-digit ISIC (revision 3) level and a proportionality assumption as in Trefler and Zhu (2010) to contruct the full 116 by 166 IO matrix. We discuss this in detail now.

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

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

[64]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 does 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, X_{po}^j, π_{op}^j, and π_{pp}^j

From our notation in the main text, recall that X_{ni}^j is sales from i to n of good j. The empirical strategy outlined in section 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.[65] 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

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

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

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_{oi}^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 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 (A32) and (A33) that do not appear in (A17). To solve this, we impose 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 (A32).

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} is 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.[66] Similar to our baseline analysis, we assume that $\kappa^j_{oo} = \kappa^j_{po} = 1$. The remaining

[66] 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.

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

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

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

$$Y_{c}^{j}=Y_{o}^{j}+Y_{p}^{j} \tag{A27}$$

$$Y_{o}^{j}=\sum_{n=1}^{N}X_{no}^{j}+X_{oo}^{j}+X_{po}^{j}=X_{Wo}^{j}+X_{oo}^{j}+X_{po}^{j} \tag{A28}$$

$$Y_{p}^{j}=\sum_{n=1}^{N}X_{np}^{j}+X_{op}^{j}+X_{pp}^{j}=X_{Wp}^{j}+X_{op}^{j}+X_{pp}^{j} \tag{A29}$$

We calculate X_{pp}^{j}, i.e., total value shipment of processing sector to itself, from the customs transaction-level data. Together with the information on X_{oi}^{j}, X_{Wo}^{j}, X_{Wp}^{j}, τ_{ci}^{j}, τ_{cp}^{j}, and Y_{c}^{j}, we can solve for X_{oo}^{j}, X_{po}^{j}, X_{op}^{j}, Y_{o}^{j} and Y_{p}^{j} from equations (A25)-(A29).

F.2 Measuring λ_{o}^{j}, λ_{p}^{j}, and t_{c}^{j}

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

$$\widehat{\delta}_{o}^{j}=\ln\left(\left[\lambda_{o}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{o}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}\left[\left[\lambda_{o}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{o}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}+\left[\lambda_{p}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{p}^{j}\kappa_{op}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}\right]^{-\nu}\right) \tag{A30}$$

$$\widehat{\delta}_{p}^{j}=\ln\left(\left[\lambda_{p}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{p}^{j}\kappa_{pp}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}\left[\left[\lambda_{o}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{o}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}+\left[\lambda_{p}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{p}^{j}\kappa_{pp}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}\right]^{-\nu}\right) \tag{A31}$$

$$\widehat{\delta}_{o}^{j,x}=\ln\left(\left[t_{o}^{j}\right]^{-\theta^{j}}\left[\frac{\left[\lambda_{o}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{o}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}+\left[\lambda_{p}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{p}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}}{\left[\lambda_{o}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{o}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}+\left[\lambda_{p}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{p}^{j}\kappa_{op}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}}\right]^{-\nu}\right) \tag{A32}$$

$$\widehat{\delta}_{p}^{j,x}=\ln\left(\left[t_{p}^{j}\right]^{-\theta^{j}}\left[\kappa_{pp}^{j}\right]^{\frac{\theta^{j}}{1-\nu}}\left[\frac{\left[\lambda_{o}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{o}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}+\left[\lambda_{p}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{p}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}}{\left[\lambda_{o}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{o}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}+\left[\lambda_{p}^{j}\right]^{\frac{1}{1-\nu}}\left[c_{p}^{j}\kappa_{pp}^{j}\right]^{-\frac{\theta^{j}}{1-\nu}}}\right]^{-\nu}\right) \tag{A33}$$

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

To simply the illustration, we introduce the new notation $\kappa_{ni}^j = t_i^j \tilde{\kappa}_{ni}^j$. By definition $\tilde{\kappa}_{ni}^j = (1+\tau_{ni}^j)(d_{ni}^j)^{\beta_j}$. With parameters θ_j, ν, $\gamma_{0,n}^j$, $\gamma_{1,n}^j$, γ_n^{jk}, α^j, L_n and K_n, and estimates of $\tilde{\lambda}_n^j \equiv \frac{\lambda_i^j}{\lambda_{us}^j}$, $\tilde{\kappa}_{ni}$, and $\frac{t_i^j}{t_{us}^j}$ $(i = 1,...,N)$, 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 = \dfrac{\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 = \dfrac{(\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}}} \dfrac{\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 = \dfrac{(\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}}} \dfrac{\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. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do. Row (3) allows processing firms to sell to to the ordinary sector and to the processing sector but loses their tariff exemption. Row (4) is the same as row (3) but processing keeps its tariff exemption. Row (5) imposes infinite trade costs on all shipments out of the processing sector. Real factor income=wage+capital income. Real income equals 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. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do. Row (3) allows processing firms to sell to to the ordinary sector and to the processing sector but loses their tariff exemption. Row (4) is the same as row (3) but processing keeps its tariff exemption. Row (5) imposes infinite trade costs on all shipments out of the processing sector. Real factor income=wage+capital income. Real income equals 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. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do. Row (3) allows processing firms to sell to to the ordinary sector and to the processing sector but loses their tariff exemption. Row (4) is the same as row (3) but processing keeps its tariff exemption. Row (5) imposes infinite trade costs on all shipments out of the processing sector. Real factor income=wage+capital income. Real income equals 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. Outcomes are normalized to 1. Row (2) imposes that processing firms pay the same tariffs on imports that ordinary firms do. Row (3) allows processing firms to sell to to the ordinary sector and to the processing sector but loses their tariff exemption. Row (4) is the same as row (3) but processing keeps its tariff exemption. Row (5) imposes infinite trade costs on all shipments out of the processing sector. Real factor income=wage+capital income. Real income equals wage+capital income+tariff revenue. $\theta^j = 4$ and $\nu^j = 0.72$.