Competition and Gains from Trade: A Quantitative Analysis of China Between 1995 and 2004

Wen-Tai Hsu   Yi Lu   Guiying Laura Wu*†

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Abstract

This paper provides a quantitative analysis of gains from trade for China over the period of 1995–2004, which was when China's openness drastically improved . We decompose gains from trade in two ways. First, we disentangle pro-competitive effects from a traditional Ricardian effect. Second, we separate the effect due to tariff reductions from that due to reductions in non-tariff trade costs. Our quantitative analysis shows that the pro-competitive effects account for 25.4% of the total welfare gains from trade, whereas the allocative efficiency alone accounts for 22.3%. We also find that tariff reductions account for about 31.6% of reductions of overall trade costs, whereas the associated relative contribution to overall gains is slightly larger at 39.6%. In our multi-sector analysis, we find that when a sectoral markup is higher in 1995, there tends to be a larger reduction in the respective sectoral trade cost between 1995 and 2004, a tendency that is generally welfare improving. One methodological advantage of this paper's quantitative framework is that its application is not constrained by industrial or product classifications, and so it can be applied to countries of any size.

*Hsu: School of Economics, Singapore Management University. 90 Stamford Road, Singapore 178903. Email: wentaihsu@smu.edu.sg; Lu: Department of Economics, National Singapore of Singapore. 1 Arts Link, Singapore, 117570. Email: ecsluyi@nus.edu.sg; Wu: Division of Economics, School of Humanities and Social Sciences, Nanyang Techonological University. 14 Nanyang Drive, Singapore 637332. Email: guiying.wu@ntu.edu.sg.

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1 Introduction

It is well understood that competition may affect gains from trade via changes in the distribution of markups.[1] For example, in the event of trade liberalization, *allocative efficiency* may improve if the dispersion of markups is reduced. This is because when markups are the same across all goods, first-best allocative efficiency is attained, as the condition that the price ratio equals the marginal cost ratio, for any pair of goods, holds. With markup dispersion, firms with low markups may produce/employ more than optimal whereas those with high markups may produce/employ less than optimal. Moreover, the average level of markups also matter because welfare improves when consumers benefit from lower markups of the goods they consume and when producers gain from higher markups (hence higher profits) in foreign markets. Jointly, these effects of level and dispersion of markups can be termed *pro-competitive effects of trade.*

This paper aims to provide quantitative analyses of gains from trade for China over the period of 1995–2004, which was when China drastically improved openness, partly due to joining World Trade Organization (WTO) at the end of 2001.[2] We will focus on the decomposition of welfare gains by disentangling pro-competitive effects from a traditional Ricardian effect to gauge its relative importance. The main effect of entry to the WTO is tariff reductions,[3] but numerous other factors may have also improved China's openness.[4] Thus, we are also interested in quantitatively separating the effect due to tariff reductions from that due to reductions in non-tariff trade costs. As entry to the WTO also involve some deregulations, the effect of tariff reduction provides a lower bound of the effect due to the WTO.

Our point of departure is two-fold. First, Brandt, Van Biesebroeck, Wang and Zhang (2012) and Lu and Yu (2015) have both estimated firm-level markups using Chinese manufacturing data and the approach by De Loecker and Warzynski (2012; henceforth DLW). Lu and Yu (2015) show that the larger the tariff reduction due to the WTO entry in one industry, the greater the reduction in the dispersion of markups in that industry. Brandt et al. present similar results on levels of markups. Their results hint at the existence of

[1] For examples of theoretical analyses of how trade may affect welfare through markups, see Devereux and Lee (2001), Epifani and Gancia (2011), Holmes et al. (2014) and Arkolakis et al. (2015).

[2] Between 1995 and 2004, the import share increased from 0.13 to 0.22, whereas the export share increased from 0.15 to 0.25. The proportion of exporters among manufacturing firms increased from 4.4% to 10.5%.

[3] As a condition to the entry to WTO (and its earlier form, GATT), China was required to lower tariffs even before entry. The tariffs were reduced substantially between 1992 and 1997. Another round of tariff reductions took place after 2001 to carry out its promise to WTO members.

[4] These factors include, for instance, developing infrastructure, including various seaports and airports and their inland connections, and expanding the education system, which accumulated human capital which facilitates communications with the rest of the world.

pro-competitive effects, but a formal welfare analysis is warranted.[5]

Second, Edmond, Midrigan and Xu (2015) have also provided a quantitative analysis of pro-competitive effects of trade using data from Taiwanese manufacturing firms and Atkeson and Burstein's model (2008), which features heterogeneous-product Cournot competition. Their model has a sensible feature that links markups with firms' market shares. The Taiwanese data works well for their oligopoly environment because they can go down to very fine product level to look at a few firms to examine their market shares. However, it could be difficult to apply their framework to a large economy (such as the US, Japan or China) where even in the finest level of industry or product, there may be hundreds of firms so that firms' market shares are typically much smaller compared with a similar data set for a small country. The problem here is that when firms' market shares are "diluted" by country size for a given industry or product category, so are pro-competitive effects. This is not to say that pro-competitive effects do not exist in large countries; rather, it may be that there are actually several markets in an industry or product category, but we simply do not know how to separate them. In light of this problem, we propose an alternative framework that does not tie markups with industrial/product classifications, and therefore could be applied to data from countries of any size.

We build our quantitative framework on the model by Bernard, Eaton, Jensen and Kortum (2003; henceforth BEJK). To help understand, we note three features of BEJK. First, the productivity of firms is heterogeneous and follows Frechét distribution, which can differ across countries. Second, firms compete in Bertrand fashion market by market with active firms charging prices at the second lowest marginal costs. Third, although differences in markups are driven by productivity differences through limit pricing, it turns out that the resulting markup distribution is invariant to the trade cost. Later, Holmes, Hsu and Lee (2014) find that this invariance is due to the assumption that the productivity distribution is fat-tailed (Frechét). If productivity draws are from a non-fat-tailed distribution, then the distribution of markups may change with the trade cost, and pro-competitive effects of trade may be observed.

Following the above discussion, we examine the distribution of markups in China in 1995 and 2004, which are shown in Figure 1. The distributions are highly skewed to the right, and it is clear that the distribution in 2004 is more condensed than that in 1995. Indeed, the (unweighted) mean markup decreases 1.43 to 1.37 and the standard deviation decreases from 0.50 to 0.48.[6] Under the BEJK structure, this suggests that one needs to deviate from

[5] For a survey of earlier evidence of the impact of foreign competition on markups, see Tybout (2003).

[6] The harmonic means weighted by revenue are 1.259 and 1.229 for 1995 and 2004, respectively. The above-mentioned pattern also exists when we break the sample into exporters and non-exporters. For details of markup estimations, see Section 3.

fat-tailed distributions to account for such changes.

We adapt the BEJK variant by Holmes et al. (2014) by adding the following parameterization: we assume that productivity draws are from log-normal distributions and that the number of firms per product is a random realization from Poisson distribution. The log-normal distribution has been widely used in empirical applications, and the Poisson parameters provide a parsimonious way to summarize the overall competitive pressure (or entry effort) in the economy.[7] As the firms observed in the data are supposed to be those that survive the Bertrand competition, it is the latent competitors that drive the markups, and hence markups are not tied to other active firms in a given industrial/product category.

The main data sets we use are Chinese firm-level data from the Economic Censuses in 1995 and 2004. We choose these two years because they are the Economic Census years before and after entry to the WTO. We prefer using the Economic Census rather than the commonly used annual survey data that reports only firms with revenues of at least 5 million renminbi. Since we are concerned with potential resource misallocation in markup channels, it is important to have data on the entire distribution, instead of using a truncated one.

Because the model is static and because we would like to remain agnostic about how the underlying environment changes over time, we estimate all parameters in each data year separately, as if we are taking snapshots of the Chinese economy in the respective years. This is important because we can then gauge the effect of "actual improvement in openness" via the change in the estimated trade cost and conduct corresponding welfare analysis. As we focus on competition, our empirical implementation relies heavily on markups. We first estimate firm-level markups following DLW and then use moments of markups to discipline model parameters, along with the moments of trade flows, active number of firms, and fraction of exporters.

The model performs well as the macro variables reproduced by the estimated model are similar in magnitude to the data counterparts. Moreover, the pattern of changes in the parameters between 1995 and 2004 are strikingly consistent with well-known facts about the Chinese economy during this period. The estimated trade friction drops significantly from 1995 to 2004, while the Poisson entry parameters also increase, reflecting the fact that not only China becomes more open, but its markets also become more competitive. The mean productivity in China relative to the rest of the world (ROW) also increases significantly, and this is consistent with the high growth rate of China during this period.

To gauge the gains from trade between 1995 and 2004, we conduct a counter-factual

[7] For examples of applications of log-normal distribution, see Cabral and Mata (2003) and Head, Mayer, and Thoenig (2014). Another non-fat-tailed distribution that is often used is bounded Pareto, e.g. Helpman, Melitz and Rubinstein (2008) and Melitz and Redding (2015). Eaton, Kortum and Sotelo (2013) also model finite number of firms as a Poisson random variable, but for a very different purpose.

analysis based on 2004 estimates but revert the trade cost back to the level estimated using 1995 data. The gain from trade is about 9.4%, and the relative contribution of the overall pro-competitive effect is 25.4% of the total gains. The improvement of allocative efficiency accounts for 22.3% of the total gains, whereas the markup level effect accounts for the remaining 3.1%. This sends two messages: (1) Significant resource misallocation is reflected in the markup dispersion; (2) Although both producers' and consumers' mean markups decreased with trade liberalization, the decrease in consumers' mean markup was larger, causing a positive effect due to levels. But, such an effect is much smaller when compared to resource misallocation. Another counter-factual is to compare with autarky, and the relative contribution of pro-competitive effects remains similar. We also conduct a series of alternative estimations and counter-factual analyses to gauge the robustness of our benchmark result. This includes a symmetric-country model, an alternative measure of markups, and a counter-factual analysis based on 1995 estimates. Among these cases, the relative contribution of pro-competitive effects ranges between 19.4% and 31.4%.

For the second decomposition, we first calculate average tariffs facing China (including both import and export tariffs), weighted by trade volumes. The average tariff drops from 15.7% to 4.3% between 1995 and 2004. Using the estimated trade costs, we decompose them into tariff and non-tariff trade costs. Despite entry to the WTO being such a major event, our calculation shows that tariff reductions account for only 31.6% of reductions of overall trade costs, whereas the associated relative contribution to overall gains is slightly larger at $35 \sim 40\%$. In other words, tariff reductions are a significant contributing factor in enhancing China's openness, but are less important than the reduction in non-tariff trade frictions.

The framework in this paper can be easily extended to a multi-sector economy, and we do this to account for various heterogeneity across sectors. The welfare results in the multi-sector economy remain similar to the one-sector economy, with the relative contribution of the pro-competitive effects and tariff reductions around 20% and 35%, respectively. Exploiting the variations in sectoral markups and trade costs, we attempt to answer the question of whether China trade-liberalized the "right" sectors? The rationale is that the overall allocative efficiency would be better improved if the government targets its trade liberalization more in the higher-markup sectors because this would reduce the dispersion of markups across sectors. We find that when a sectoral markup was higher in 1995, there was a tendency for a larger reduction in the estimated trade cost or import tariff between 1995 and 2004.

Besides related studies already discussed, our literature review starts with Arkolakis, Costinot and Rodriguez-Clare (2012; henceforth ACR), who show that there is a class of influential trade models in which the welfare measure can be summarized by a simple statistic that depends only on domestic expenditure share and trade elasticity. This class includes

BEJK and features no pro-competitive effects. By using Holmes et al. (2014), our welfare formula extends the ACR formula in the sense that a *productive efficiency index* closely traces the ACR statistic, and that the pro-competitive effects enter as two multiplicative terms.[8]

Whereas Edmond et al. (2015) and this paper adopt oligopolistic approaches to study pro-competitive effects of trade, another approach is to couple monopolistic competition with a non-CES preference, and this includes Ottaviano, Tabuchi and Thisse (2002), Melitz and Ottaviano (2008), Behrens and Murata (2012), Feenstra (2014), and Arkolakis, Costinot, Donaldson, and Rodriguez-Clare (2015). In particular, Arkolakis et al. show that pro-competitive effects are "elusive", and Feenstra shows that the pro-competitive effects could emerge when productivity draws are from a bounded distribution. Note that the economics of the pro-competitive effects are very different in a monopolistic competition model than in the oligopoly model we consider. In monopolistic competition, a change in the trade cost only affects a domestic firm through general equilibrium effects that might shift or rotate the firm's demand curve. In contrast, in a Bertrand environment, the pro-competitive force of trade operates at the level of the particular good, not through general equilibrium.[9]

Our work is also related to Atkeson and Burstein (2008), de Blas and Russ (2012), and Goldberg, De Loecker, Khandelwal and Pavcnik (2015), who provide analyses of how trade affects the distribution of markup. Our work is different from these papers in that our focus is on quantitative welfare analysis. This paper also relates to the literature on the welfare impact of China's growth and trade integration, e.g. Song, Storesletten and Zilibotti (2011), di Giovanni, Levchenko and Zhang (2014) and Hsieh and Ossa (2015). The literature discussion above focuses specifically on trade. We note our paper is also part of a broader literature on how allocative efficiency affects aggregate productivity, including Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and Peters (2012).

The rest of the paper is organized as follows. Section 2 lays out the model; Section 3 explains the data and quantifies the model; Section 4 presents the results on counter-factual analyses; Section 5 extends the model to multiple sectors; and Section 6 concludes.

[8] If markups were a constant, then the pro-competitive terms drop out, reducing the welfare measure to the ACR statistic. It is worth noting that trade may sometimes affect welfare without observed trade flows. For example, Salvo (2010) and Schmitz (2005) show that the threat of competition from imports can influence domestic outcomes, even if in the end, the imports don't come in.

[9] Other recent studies on gains from trade via different angles from the ACR finding include at least Melitz and Redding (2015) on re-examining the selection effect in gains from trade and an additional effect due to thinner tails (bounded Pareto); Caliendo and Parro (2015) on the roles of intermediate goods and sectoral linkages; and di Giovanni, Levchenko, and Zhang (2014) on the global welfare impact of China's trade integration and productivity growth. Our work differs in that we focus on the pro-competitive effects.

2 Model

2.1 Consumption and Production

There are two countries, which are indexed by $i = 1, 2$. In our empirical application, 1 means China, and 2 means the ROW. As is standard in the literature of trade, we assume a single factor of production, labor, that is inelastically supplied, and the labor force in each country is denoted as L_i. There is a continuum of goods with measure γ, and the utility function of a representative consumer is

$$Q = \left(\int_0^{\bar{\omega}} (q_\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \quad \text{for } \sigma > 1,$$

where q_ω is the consumption of good ω, σ is the elasticity of substitution, and $\bar{\omega} \leq \gamma$ is the measure of goods that are actually produced. We will specify how $\bar{\omega}$ is determined shortly. The standard price index is

$$P_j \equiv \left(\int_0^{\bar{\omega}} p_{j\omega}^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}.$$

Total revenue in country i is denoted as R_i, which also equals the total income. Welfare of country i's representative consumer is therefore R_i/P_i, which can also be interpreted as real GDP. The quantity demanded ($q_{j\omega}$) and expenditure ($E_{j\omega}$) for the product ω in country j are given by

$$\begin{aligned} q_{j\omega} &= Q_j \left(\frac{p_{j\omega}}{P_j} \right)^{-\sigma}, \\ E_{j\omega} &= R_j \left(\frac{p_{j\omega}}{P_j} \right)^{1-\sigma}, \end{aligned}$$

and $\phi_{j\omega} \equiv \left(\frac{p_{j\omega}}{P_j} \right)^{1-\sigma}$ is country j's spending share on the good ω.

For each good ω, there are n_ω number of potential firms. Production technology is constant returns to scale, and for a firm k located at i, the quantity produced is given by

$$q_{\omega,ik} = \varphi_{\omega,ik} \ell_{\omega,ik},$$

where $\varphi_{\omega,ik}$ is the Hicks-neutral productivity of firm $k \in \{1, 2, ..., n_{\omega,i}\}$, $n_{\omega,i}$ is the number of entrants in country i for good ω, and $\ell_{\omega,ik}$ is the amount of labor employed. Note the subtle and important difference between subscript $j\omega$ and ω, i. The former means that it is the purchase of ω by consumers at location j, and the latter is the sales or production characteristics of the firm located at i producing ω.

2.2 Measure of Goods and Number of Firms

The number of firms for each good $\omega \in [0, \gamma]$ in each country i is a random realization from a Poisson distribution with mean λ_i. That is, the density function is given by

$$f_i(n) = \frac{e^{-\lambda_i} \lambda_i^n}{n!}.$$

The total number of firms for good ω across the two countries is $n_\omega = n_{\omega,1} + n_{\omega,2}$. There are goods that have no firms from either countries, and the total number of goods actually produced is given by

$$\bar{\omega} = \gamma \left[1 - f_1(0) f_2(0)\right] = \gamma \left[1 - e^{-(\lambda_1 + \lambda_2)}\right]. \tag{1}$$

There is also a subset of goods produced by only one firm in the world, and in this case, this firm charges monopoly prices in both countries. For the rest, the number of firms in the world are at least two, and firms engage in Bertrand competition. We do not model entry explicitly. By this probabilistic formulation, we let λ_i summarize the entry effort in each country. From (1), we see that the larger the mean numbers of firms λ_i, the larger the $\bar{\omega}$.

2.3 Productivity, Trade Cost, Pricing and Markups

Let wages be denoted as w_i. If the productivity of a firm is $\varphi_{i\omega}$, then its marginal cost is $w_i/\varphi_{i\omega}$ before any delivery. Assume standard iceberg trade costs $\tau_{ij} \geq 1$ (to deliver one unit to j from i, it will need to ship τ_{ij} units). Let $\tau_{ii} = 1$ for all i. Hence, for input ω, the delivered marginal cost from country i's firm k to country j is therefore $\frac{\tau_{ij} w_i}{\varphi_{\omega,ik}}$. For each $i\omega$, productivity $\varphi_{\omega,ik}$ is drawn from log-normal distribution, i.e., $\ln \varphi_{\omega,ik}$ is distributed normally with mean μ_i and variance η_i^2. Let $\varphi_{\omega,i}^*$ and $\varphi_{\omega,i}^{**}$ be the first and second highest productivity draws among the $n_{i\omega}$ draws.

For each ω, the marginal cost to deliver to location 1, for the two lowest cost producers at 1, and the two lowest cost producers at 2, are then

$$\left\{ \frac{\tau_{1j} w_1}{\varphi_{\omega,1}^*}, \frac{\tau_{1j} w_1}{\varphi_{\omega,1}^{**}}, \frac{\tau_{2j} w_2}{\varphi_{\omega,2}^*}, \frac{\tau_{2j} w_2}{\varphi_{\omega,2}^{**}} \right\}.$$

If the number of firms is 1, 2, or 3, then we can simply set the missing element in the above set to infinity. Let $a_{j\omega}^*$ and $a_{j\omega}^{**}$ be the lowest and second lowest elements of this set. The monopoly pricing for goods sold in country j is $\bar{p}_{j\omega} = \frac{\sigma}{\sigma-1}a^{*}_{j\omega}$. In the equilibrium outcome of Bertrand competition, price will equal the minimum of the monopoly price and the marginal cost $a^{**}_{j\omega}$ of the second lowest cost firm to deliver to j, i.e.

$$p_{j\omega} = \min\left(\bar{p}_{j\omega}, a^{**}_{j\omega}\right) = \min\left\{\frac{\sigma}{\sigma-1}a^{*}_{j\omega}, a^{**}_{j\omega}\right\}.$$

The markup of good ω at j is therefore

$$m_{j\omega} = \frac{p_{j\omega}}{a^{*}_{j\omega}} = \min\left\{\frac{\sigma}{\sigma-1}, \frac{a^{**}_{j\omega}}{a^{*}_{j\omega}}\right\}.$$

Note that firms' markups may differ from the markups for consumers. A non-exporter's markup is the same as the one facing consumers, but an exporter has one markup for each market. Let the markup of an exporter producing ω be denoted as m^{f}_{ω}. Then, due to constant returns to scale,

$$m^{f}_{\omega} = \left(\frac{\text{costs}}{\text{revenue}}\right)^{-1} = \left(\frac{E_{1\omega}}{E_{1\omega}+E_{2\omega}}m^{-1}_{\omega,1} + \frac{E_{2\omega}}{E_{1\omega}+E_{2\omega}}m^{-1}_{\omega,2}\right)^{-1}.$$

In other words, an exporter's markup is a harmonic mean of the markups in each market, weighted by relative revenue.

We can now define *producers' aggregate markup*, M^{sell}_{i}. Let $\chi^{*}_{j}(\omega) \in \{1,2\}$ denote the source country for any particular good ω at destination j. Then, we have

$$\begin{aligned} M^{sell}_{i} &= \frac{R_i}{w_i L_i} = \frac{\int_{\{\omega:\, \chi^{*}_{1}(\omega)=i\}} \phi_{1\omega} R_1 d\omega + \int_{\{\omega:\, \chi^{*}_{2}(\omega)=i\}} \phi_{2\omega} R_2 d\omega}{\int_{\{\omega:\, \chi^{*}_{1}(\omega)=i\}} m^{-1}_{1\omega}\phi_{1\omega} R_1 d\omega + \int_{\{\omega:\, \chi^{*}_{2}(\omega)=i\}} m^{-1}_{2\omega}\phi_{2\omega} R_2 d\omega} \\ &= \left(\int_{\{\omega:\, \chi^{*}_{1}(\omega)=i\}} m^{-1}_{1\omega}\frac{\phi_{1\omega}R_1}{R_i}d\omega + \int_{\{\omega:\, \chi^{*}_{2}(\omega)=i\}} m^{-1}_{2\omega}\frac{\phi_{2\omega}R_2}{R_i}d\omega\right)^{-1}, \end{aligned} \tag{2}$$

which is the revenue-weighted harmonic mean of markups of all goods with *source* at location i. Similarly, *consumers' aggregate markup* M^{buy}_{i} is the revenue-weighted harmonic mean across goods with *destination* at i:

$$M^{buy}_{i} = \left(\int_{0}^{\bar{\omega}} m^{-1}_{i\omega}\phi_{i\omega}d\omega\right)^{-1}.$$

Let the inverses of markups be called cost shares, as they are the shares of costs in revenues. A harmonic mean of markups is the inverse of the weighted arithmetic mean of cost shares. Harmonic means naturally appear here precisely because the weights are revenue.

However, it is unclear how a harmonic variance could be defined. Since the (arithmetic) variance of markup is positively related to the variance of cost shares, we choose to work with cost shares in calculating moments for our empirical work.

2.4 Wages and General Equilibrium

Labor demand in country i from a non-exporter that produces input ω is

$$\ell_{\omega,i} = \frac{q_{i\omega}}{\varphi^*_{\omega,i}} = \frac{1}{\varphi^*_{\omega,i}} \frac{R_i}{P_i} \left(\frac{p_{i\omega}}{P_i} \right)^{-\sigma}.$$

For an exporter at i, its labor demand is

$$\begin{aligned} \ell_{\omega,1} &= \frac{q_{1\omega} + \tau q_{2\omega}}{\varphi^*_{\omega,1}} = \frac{1}{\varphi^*_{\omega,1}} \left[\frac{R_1}{P_1} \left(\frac{p_{1\omega}}{P_1} \right)^{-\sigma} + \frac{\tau R_2}{P_2} \left(\frac{p_{2\omega}}{P_2} \right)^{-\sigma} \right] \\ \ell_{\omega,2} &= \frac{\tau q_{1\omega} + q_{2\omega}}{\varphi^*_{\omega,2}} = \frac{1}{\varphi^*_{\omega,2}} \left[\frac{\tau R_1}{P_1} \left(\frac{p_{1\omega}}{P_1} \right)^{-\sigma} + \frac{R_2}{P_2} \left(\frac{p_{2\omega}}{P_2} \right)^{-\sigma} \right]. \end{aligned}$$

Labor market clearing in country i is

$$\int_{\omega \in \chi_i} \ell_{\omega,i} d\omega = L_i, \tag{3}$$

where χ_i is the set of ω produced at i.

To calculate the trade flows, observe that the total exports from country i to country j is

$$R_{j,i} = \int_{\{\omega:\, \chi^*_j(\omega)=i\}} E_{j\omega} d\omega = R_j \int_{\{\omega:\, \chi^*_j(\omega)=i\}} \left(\frac{p_{j\omega}}{P_j} \right)^{1-\sigma} d\omega.$$

where $\chi^*_j(\omega) \in \{1,2\}$ denotes the source country for any particular good ω at destination j. The balanced trade condition is therefore

$$R_{2,1} = R_{1,2}. \tag{4}$$

We choose country 1's labor as numeraire, and hence $w_1 = 1$, and $w \equiv w_2$ is also the wage ratio. Given $\{w, R_1, R_2\}$, the realization of $n_{i,\omega}$ for each i and ω, and the realization of $\{\varphi_{\omega,ik}\}$ for each firm $k \in \{1, 2, ..., n_{i,\omega}\}$, pricing, markups, consumption decisions, labor demand, and trade flows are all determined as described above. The two labor market clearing conditions in (3) and the balanced trade condition (4) thus determine $\{w, R_1, R_2\}$. For easier computation for our quantitative work, we use an algorithm of equilibrium computation that reduces the above-mentioned system of equations to one equation in one unknown. We describe such an algorithm in Appendix A1.

2.5 Welfare

This subsection shows how welfare is decomposed into different components. The welfare decomposition is exactly that provided by Holmes et al. (2014). Here, we try to be brief and at the same time self-contained. Let A_i be the price index at i when all goods are priced at marginal cost:

$$A_i = \int_0^{\bar{\omega}} a^*_{i\omega} \tilde{q}^a_{i\omega} d\omega,$$

where $\tilde{\mathbf{q}}^a_i = \{\tilde{q}^a_{i\omega} : \omega \in [0, \bar{\omega}]\}$ is the expenditure-minimizing consumption bundle that delivers one unit of utility. Obviously, the product of producers' aggregate markup and labor income entails total revenue (2), and we can write welfare at location i as

$$\begin{aligned} W_i^{Total} &= \frac{R_i}{P_i} = w_i L_i \times M_i^{sell} \times \frac{1}{P_i} \\ &= w_i L_i \times \frac{1}{A_i} \times \frac{M_i^{sell}}{M_i^{buy}} \times \frac{A_i \times M_i^{buy}}{P_i} \\ &\equiv w_i L_i \times W^{Prod} \times W^{TOT} \times W^A. \end{aligned}$$

Without loss of generality we will focus on the welfare of country 1, and by choosing numeraire, we can let $w_1 = 1$. As the labor supply L_i will be fixed in the analysis, the first term in the welfare decomposition is a constant that we will henceforth ignore. The second term $1/A_i$ is the *productive efficiency index* W^{Prod}, and this is what the welfare index would be with constant markup. The index varies when there is technical change determining the underlying levels of productivity. It also varies when trade costs decline, decreasing the cost for foreign firms to deliver goods to the domestic country. Terms-of-trade effects also show up in W^{Prod} because a lower wage from a source country will raise the index. It can be shown that this term traces the ACR statistics closely in terms of its elasticity with respect to trade costs.

The third term is a "terms of trade" effect on markups (W^{TOT}) that depends on the ratio of producers' aggregate markup to consumers' aggregate markup. Alternatively, we call it markup level effect. This term is intuitive because a country's welfare improves when its firms sell goods with higher markups while its consumers buy goods with lower markups. This term drops out in two special cases: under symmetric countries where the two countries are mirror images of each other; and under autarky, as there is no difference between the two aggregate markups.

The fourth term is the *allocative efficiency index* W^A

$$W_i^A \equiv \frac{A_i \times M_i^{buy}}{P_i} = \frac{\int_0^{\bar{\omega}} a_{i\omega}^* \tilde{q}_{i\omega}^a d\omega}{\int_0^{\bar{\omega}} a_{i\omega}^* \tilde{q}_{i\omega} d\omega} \leq 1.$$

The inequality follows from the fact that under marginal cost pricing, $\tilde{q}_{\omega,i}^a$ is the optimal bundle, whereas $\tilde{q}_{i\omega}$ is the optimal bundle under actual pricing. If markups are constant, then for any pair of goods, the ratio of actual prices equals the ratio of marginal cost. In this case, the two bundles become the same and $W_i^A = 1$. Once there is any dispersion of markups, welfare deteriorates because resource allocation is distorted. Goods with higher markups are produced less than optimally (employment is also less than optimal), and those with low markups are produced more than optimally (employment is also more than optimal).

Note that as Holmes et al. focus on the symmetric country case, they do not explicitly analyze the markup level effect W^{TOT}. As fitting to the Chinese economy, we allow asymmetries between countries in all aspects of the model (labor force, productivity distribution, entry and wages).

3 Quantifying the Model

We use the following two steps to quantify the model. First, we estimate the markup distribution and infer the elasticity of substitution from such distribution. Then, given σ, measures of $\{w, R_1, R_2\}$, we use moments of markups, trade flows, number of firms and fraction of exporters to estimate the remaining parameters by Simulated Method of Moments (SMM). Note that, unlike Edmond et al. (2015) whose benchmark focuses on symmetric countries, our empirical implementation focuses on asymmetric countries, as the large wage gap between China and the ROW should not be ignored since it may have a large impact on parameter estimates, as well as potential large general equilibrium effects in counter-factuals.

3.1 Data

Our firm-level data set comes from the Economic Census data (1995 and 2004) from China's National Bureau of Statistics (NBS), which covers all manufacturing firms, including state-owned enterprises (SOE). The sample sizes for 1995 and 2004 are $458,327$ and $1,324,752$, respectively.[10] The benefit of using this data set, instead of the commonly used firm-level

[10] The original data sets have larger sample sizes, but they also include some (but not all) non-manufacturing industries, as well as firms without independent accounting and village firms, which entail

survey data set, which only includes firms with revenues of at least 5 million renminbi, is that we do not have to deal with the issue of truncation. As we are concerned with potential resource misallocation between firms, it is important to have the entire distribution. We estimate the models separately for the years 1995 and 2004.

We obtain world manufacturing GDP and GDP per capita from the World Bank's World Development Indicators (WDI). The aggregate Chinese trade data is obtained from the UN COMTRADE. We also use tariff data for various purposes, including gauging the relative importance of tariff reductions in the overall reduction in trade frictions. The tariff data is obtained from World Integrated Trade Solution (WITS), which was developed by the World Bank and incorporates trade data from various sources. For our quantitative analysis, we calculate an economy-wide average tariff, and for our multiple-sector analysis, we calculate sectoral average tariffs. We provide details about the data and the method we use to calculate these average tariffs in Appendix A2.

3.2 Estimation of Markups

Under constant returns to scale assumption, a natural way to estimate markups is by taking the ratio of revenue to total costs, i.e., revenue productivity, or what we call *raw markup*. However, it is important to recognize that, in general, raw markups may differ across firms, not only because of the real markup differences, but also because of differences in the technology with which they operate. To control for this potential source of heterogeneity, we use modern IO methods to purge our markup estimates of the differences in technology. In particular, we estimate markups following DLW's approach,[11] who calculate markups as

$$m_\omega = \frac{\theta_\omega^X}{\alpha_\omega^X},$$

where θ_ω^X is the input elasticity of output for input X, and α_ω^X is the share of expenditure on input X in total revenue. To map our model into firm-level data, we relax the assumptions of a single factor of production and constant returns to scale. Following DLW, we assume a translog production function.[12] The estimation of firm-level markup hinges on choosing an input X that is free of any adjustment costs, and the estimation of its output elasticity

numerous missing values. The final sample is obtained from excluding these cases and adjusting for industrial code consistency.

[11] We also conduct estimation and counter-factual analysis under raw markups as a robustness check.

[12] In our implementation of the DLW approach using Chinese firm-level data under translog production function, which allows variable returns to scale, it turns out that the returns to scale are quite close to constant. See Table A1 in the appendix. Interestingly, Edmond et al. (2015) also found similar results using Taiwanese firm-level data.

θ_{ω}^{X}. As labor is largely not freely chosen in China (particularly state-owned enterprises) and capital is often considered a dynamic input (which makes its output elasticity difficult to interpret), we choose intermediate materials as the input to estimate firm markup (see also DLW). The full details of the markup estimation are relegated to Appendix A3.

Table 1 gives summary statistics of the markup distribution,[13] with breakdowns in each year and between exporters and non-exporters. Observe that the (unweighted) mean markups all decrease between 1995 and 2004 for all firms, both exporters and non-exporters. The (unweighted) standard deviation of markups decreases for non-exporters, but increases slightly for exporters. Because there are more non-exporters than exporters and the decrease in non-exporters' standard deviation is larger than the increase in exporter's standard deviation, the overall standard deviation decreases. Almost all of the percentiles decreased between 1995 and 2004. This is consistent with the pattern seen in Figure 1 where the entire distribution becomes more condensed.

However, we note that the pattern described in Table 1 only hints at the existence of pro-competitive effects. The reduction of dispersion of firm markups does not necessarily mean that the allocative efficiency increases because allocative efficiency depends on consumers' markups rather than firms' markups. It does show that the markets facing Chinese firms become more competitive. Also, we cannot reach a conclusion yet about the markup level effect, as we do not observe the consumers' aggregate markup directly. We need to quantify the model and simulate both types of markups to conduct welfare analysis.

3.3 Elasticity of Substitution

As a preference parameter, we infer a common elasticity of substitution σ for both years. Note that the model implies that $m \in \left[1, \frac{\sigma}{\sigma-1}\right]$, and hence the monopoly markup is the upper bound of markup distribution. Recall the economics behind this. An active firm of a product charges the second lowest marginal cost when such cost is sufficiently low. When the second marginal cost is high, the markup is bounded by the monopoly markup because the firm's profit is still subject to the substitutability between products. The higher the substitutability (σ), the lower the monopoly markup the firm will charge.

As we examine the effects of markups, we infer σ using the upper bound of the markup distribution. Considering the possibility of measurement errors and outliers, we equate $\sigma/(\sigma-1)$ to the 99th percentile of estimated markup distribution (using the pooled sample

[13]Following the literature, e.g., Goldberg, De Loecker, Khandelwal and Pavcnik (2015) and Lu and Yu (2015), we trim the estimated markup distribution in the top and bottom 2.5 percentiles to alleviate the concern that the extreme outliers may drive the results. Our results are robust to alternative trims (e.g, the top and bottom 1%; results are available upon request). We also drop estimated markups that are lower than one, as our structural model does not generate such markups.

from 1995–2004). We obtain that $\sigma = 1.40$, which reflects that the 99th percentile is around 3.5.[14]

Note that the inferred σ here is quite different from the literature, which typically estimates σ under monopolistic competition models that often feature constant markups. Under a constant-markup model and using the harmonic mean of firm markups in 1995, 1.259, this implies $\sigma = 4.86$. However, in the current model, this value of σ implies that $m \in [1, 1.259]$, which will cut 50.6% off the estimated markup distribution. Then, these large markups where most distortions come from are ignored. In fact, the pro-competitive effects of trade become negligible under $m \in [1, 1.259]$ because the associated allocative efficiency is much closer to the first-best case (constant markup) without the very skewed larger half of the markups. Edmond et al. (2015) also found that the extent of pro-competitive effects depends largely on the extent to which markups can vary in the model. After all, estimations/calibrations should be model specific, and $\sigma/(\sigma-1)$ in our model is the upper bound rather than the average of markups.

3.4 Simulated Method of Moments

We estimate the remaining parameters using SMM for 1995 and 2004 separately.

To calculate $w = w_2/w_1$, we first obtain the GDP per capita of China and the ROW from WDI.[15] We then calculate w_i by multiplying GDP per capita by the labor income shares for the ROW and China, which are taken from Karabarbounis and Neiman (2014).[16] For R_1 and R_2, we first obtain the manufacturing GDPs of China and the ROW from WDI data. We then use the input-output table for China (2002) and the US (1997–2005) to obtain GDP's share of total revenue. We then use such shares and the manufacturing GDPs to impute R_1 and R_2 as total revenue. Although our model does not distinguish value added and revenue, we choose to interpret R_i as total revenue rather than GDP to be consistent with our export and import moments, which are also in terms of revenue.

Given $\{w, R_1, R_2\}$, σ, and all the remaining parameters, we can simulate various moments in the model. For $i = 1, 2$, the remaining parameters are

[14] Note that this estimate of σ is not sensitive to sample size. In our multi-sector exercise, σ_s is separately inferred for each sector s using the markup distribution of that sector. The unweighted mean of σ_s is 1.44, and 23 out of 29 σ_s are within one standard deviation from the mean, $(1.27, 1.61)$. See Section 5.1.

[15] The ROW's GDP per capita is the population-weighted average of GDP per capita across all countries other than China.

[16] The ROW's labor share is the weighted average of labor share across all countries besides China, with the weight being relative GDP.

τ :	trade cost
γ :	total measure of goods
λ_i :	mean number of firms per product
μ_i :	mean parameter of log-normal productivity draw
η_i :	standard deviation parameter of log-normal productivity draw

Note that for productivity, we normalize $\mu_2 = 0$ (when $\ln \varphi$ is zero, $\varphi = 1$) because only the relative magnitude of μ_1 to μ_2 matters. Choosing μ_2 amounts to choosing a unit. In order to use SMM to estimate these seven parameters, we need at least seven moments. We use the following 12 moments: the import and export shares; relative number of firms; fraction of exporters; weighted mean and standard deviation of cost shares for both exporters and non-exporters; and the median and 95th percentile of cost shares for exporters and non-exporters.[17] We use moments of exporters and non-exporters separately because the way in which parameters of countries 1 and 2 (China and the ROW) enter these moments differ between these two groups. The intuition is clear: Chinese exporters face direct competition in the ROW's markets and non-exporters face foreign competition on their home turf. As we lack firm-level data from the ROW, this approach is crucial for backing out the parameters of the ROW. For comparison, we also estimate a symmetric country version in which case ROW's parameters are the same as China's.

Recall that the actual measure of goods is given by (1): $\bar{\omega} = \gamma \left[1 - e^{-(\lambda_1 + \lambda_2)}\right]$, but this is not directly observed. What is observable is the number of active Chinese firms:

$$N_1 = \gamma \left(1 - e^{-\lambda_1}\right) \times \Pr \left[\frac{1}{\varphi_{1\omega}^*} < \frac{w\tau}{\varphi_{2\omega}^*} \right].$$

Divide both sides by $\bar{N}$, a large number that is chosen for normalization. The moment we use is the relative number of Chinese firms:

$$\frac{N_1}{\bar{N}} = \frac{\gamma \left(1 - e^{-\lambda_1}\right)}{\bar{N}} \times \Pr \left[\frac{1}{\varphi_{1\omega}^*} < \frac{w\tau}{\varphi_{2\omega}^*} \right], \tag{5}$$

The choice of $\bar{N}$ does not affect the estimates, but we must choose the same $\bar{N}$ for both 1995 and 2004 in order to gauge the increase in γ. For this purpose, we choose $\bar{N}$ to be 2 million.

The estimation result is shown in Table 2. The model fits the data moments reasonably well, and the small standard errors indicate that each parameter is relatively precisely estimated. As we estimate the models for 1995 and 2004 separately, the changes of the parameters are strikingly consistent with well-known empirical patterns about the Chinese

[17] The import share is the import penetration ratio, i.e. IM/(R1-EX+IM), and the export share is the total export divided by the same denominator. All the cost share moments are weighted by revenues.

economy during this period. From 1995 to 2004, the estimate of τ shows a dramatic decrease from 2.31 to 1.66. The measure of goods γ more than triples from 0.26 to 0.85. This basically reflects the sharp increase in the number of firms between the two Economic Censuses, from 458,327 in 1995 to 1,324,752 in 2004, which is almost triple. The mean number of firms per product in China (λ_1) increased from 2.44 to 2.61, about 7% increase, whereas in the ROW it increased from 5.27 to 5.83, about 10.6% increase. Given that the ROW is larger than China, it may be reasonable that the ROW's Poisson entry parameter had a larger increase. China's mean log productivity (μ_1) relative to the ROW increased from -2.40 to -1.79. These numbers are negative, meaning that China's productivity is lower than that of the ROW (μ_2 is normalized to 0). Also, we see a slight decrease in the dispersion parameter of the productivity distribution in both countries (η_1, η_2). Interestingly, the productivity dispersion is larger in China than in the ROW, which is consistent with the finding by Hsieh and Klenow (2009).[18]

Based on the 2004 estimation, we calculate a Jacobian matrix in which each entry gives a rate of change of a moment to a parameter, and this is shown in Table 3. The larger the absolute value of a rate of change, the more sensitive this moment is to the parameter, and hence the more useful this moment is in identifying this parameter, at least at the local area of the optimal estimates. With such Jacobian matrices, the asymptotic variance-covariance matrices of the optimal estimates can be calculated to produce the standard errors reported in Table 2.

Trade cost τ affects almost all moments significantly, and it is natural to see that the two trade moments, the relative number of Chinese firms and the fraction of exporters are particularly strong for identifying this. Interestingly, when τ increases, the 95th percentiles of markups for both exporters and non-exporters increase sharply. For non-exporters, this is intuitive because a higher τ provides non-exporters more insulation from foreign competition, and the top non-exporters gain more from this. For exporters, a higher τ makes it harder for them to compete in foreign markets, but recall that an exporter's markup is a harmonic mean of the markups in both the domestic and foreign markets. It must be that the gains in markups at home outweigh the losses in markups in foreign markets.

For λ_1 and λ_2, the 95th percentiles of markups and the relative number of active firms are crucial in identifying these two parameters, with the trade moments playing some role

[18] The mean of a log-normal distribution is $e^{\mu+\eta^2/2}$. According to our estimates of μ_1 and η_1 in these two years, this translates to an annual productivity growth rate of 6.9%. This impressive growth rate is actually similar to the 7.96% estimated by Brandt, Van Biesebroeck and Zhang (2012). Note that the 6.9% growth rate here is relative to the ROW. If the ROW also grows in their productivity, the actual productivity growth rate could be even higher. In fact, Brandt, Van Biesebroeck, Wang, and Zhang (2012) find a 12% average TFP growth rate at industry level. The data used in both above-mentioned papers is the annual manufacturing survey data from 1998 to 2007.

as well. The intuition is as follows. Fixing other parameters, when λ_i increases, the number of entrants per product in country i increases. Due to the non-fat-tailed nature of the productivity distribution, the ratio between the top two draws is narrowed, but since this ratio is indeed the markup and since this is particularly pronounced for the top markups, the 95th percentiles are particularly useful in identifying these two parameters. The fact that we observe increases in λ_i during this period may reflect that the 95th percentiles of markups decrease during this period. Intuitively, the relative number of (active) Chinese firms is also useful for identifying λ_1, as seen clearly in (5).[19]

For the measure of goods γ, it is obvious that the relative number of Chinese firms is the most useful moment. An increase in mean productivity parameter μ_1 increases export share, the number of Chinese firms, and the fraction of exporters, but decreases the import share. These are all intuitive. However, an increase in μ_1 sharply increases the 95th percentile markup for non-exporters but sharply decreases the 95th percentile markup for exporters. This is because top non-exporters are actually not the most productive firms – their productivities are somewhere in the middle of the distribution and hence they gain in markup by having higher productivity. In contrast, top exporters are the most productive firms, and they lose in markup when they become even more productive, due to the compression at the upper tail of the productivity distribution.

For η_1 and η_2, first note that they are not only dispersion parameters, but their increases will induce increases in means as well. So, the direction of changes due to a change in η_1 is similar to that of a change in μ_1, but the intensities are quite different. For example, η_1 has much larger effects on moments of markups, including both means and standard deviations of the cost shares, than μ_1. Moreover, the 95th percentile markup for exporters is extremely sensitive to η_1 because η_1 affects the top productivities much more than μ_1. Also note the interesting pattern: η_1 and η_2 almost always affect moments in opposite ways. An increase in η_2 increases both the mean and dispersion of the ROW's productivity, and this increases China's import share, and decreases China's export share, number of firms and fraction of exporters. It decreases Chinese non-exporters' median and 95th percentile markups, but increases those of Chinese exporters.

Finally, we discuss a point that is often mentioned in studies of the Chinese economy. China underwent various reforms, including but not limited to trade reforms, in this decade. One notable reform is that of SOEs during the late 90s, which is well known to make China's various industries more competitive. Although we do not model the source of distortion

[19] Trade flows are also useful, as an increase in λ_1 raises active firms' productivities in China, increasing the export share and reducing the import share. On the other hand, an increase in λ_2 raises active firms' productivities in the ROW, increasing the import share and reducing the export share in China.

explicitly in our model and rather treat markups (and their distribution) as a reflection of distortion, the fact that we observe increases in both λ_1 and γ may be partly due to these reforms. The compression in markup distribution (Table 1 and Figure 1) and the increasing number of manufacturing firms are also consistent with the above-mentioned reforms.

4 Gains from Trade

In this section, we conduct a battery of counter-factual analyses to examine the welfare gains from trade.

4.1 Benchmark Result

For each year (1995 or 2004), given the estimated parameters and $\{w, R_1, R_2\}$ from data, we can calculate the implied labor force L_1 and L_2 using labor market clearing conditions. Then, under all estimated parameters and implied $\{L_1, L_2\}$, we can also simulate a set of $\{w, R_1, R_2\}$. The bottom three rows in Table 2 show the simulated $\{w, R_1, R_2\}$, which turn out to be quite close to the data counterpart,[20] serving as additional validation of the model.

To examine gains from trade, we conduct two counter-factual analyses by fixing all parameter values at the 2004 level and changing only τ. In the first analysis, we simulate welfare and its components when τ is changed to the 1995 level, and we calculate the percentage changes of welfare and its components. In the second analysis, we take τ to an inhibitive value so that the economy becomes autarky.

The results are shown in Table 4. The welfare gains from 1995's openness to 2004's level are 9.43%, in which the pro-competitive effects account for $(2.10+0.29)/9.39 \approx 25.4\%$. Moreover, the allocative efficiency W^A accounts for $2.10/9.39 \approx 22.3\%$ of these gains, whereas the markup level effect accounts for the remaining 3.1%. In fact, both aggregate markups M^{sell} and M^{buy} decrease during this period, which is a natural result under trade liberalization, but the percentage decrease in the consumers' aggregate markup M^{buy} is larger. Overall, although the markup level effect is positive, it is relatively small, whereas the combined effect can account for about a quarter of the total gains. The total gains from autarky to the 2004 level are, of course, much larger, at 33.4%, but the decomposition is similar to the first analysis.

Next, we examine whether the result of "diminishing returns in openness" in Edmond et al. (2015) holds here. The following table summarizes the welfare gains reported in their

[20] Here, the largest discrepancy between data values and simulated value is the total revenue of the ROW in 1995, which is about 10.5%. For all the other numbers, the discrepancies are all less than 5.2%.

study, as well as the breakdown in Ricardian gains and allocative efficiency. There is an obvious "diminishing returns" in allocative efficiency, as the opening up from autarky to 10% import share improves welfare by 1.2%, whereas further opening up from 10% to 20% improves welfare by only 0.3%. But such a diminishing-returns pattern does not show up in the Ricardian component. As a result, the relative contribution of allocative efficiency diminishes rapidly from $1.2/3.1 \approx 38\%$ to $0.3/2.8 \approx 10.7\%$.

Import share	%Δ in Edmond et al.			Importance of W^A
	Total Welfare	Ricardian	W^A	
0 to 10%	3.1	1.9	1.2	38.7%
10% to 20%	2.8	2.5	0.3	10.7%

Panel B of Table 4 reports the result from a similar exercise. Note that Edmond et al.'s pro-competitive effect only includes allocative efficiency but not the markup level effect as their formulation focuses on symmetric countries. To compare, we ignore the markup level effect. A similar diminishing returns pattern in allocative efficiency is obvious, dropping from 5.5% to 1.5%. But, unlike in Edmond et al., we also see sharp diminishing returns in our counter-factuals for total welfare and the Ricardian component. As a result, we do not see a diminishing relative contribution in allocative efficiency. Indeed, the relative contribution stays around 24%, which is quite close to the results reported in Panel A.

Looking at both panels together, the relative contribution of pro-competitive effects range from 23.3% to 27.6%, and the relative contribution of allocative efficiency ranges from 22.3% to 24.6%. Despite the differences in model structures, our estimates turn out to be in the ballpark of Edmond et al.'s estimates, which range from 11% to 38%.

Recall the welfare formula in ACR, $\frac{1}{\varsigma}\ln\left(\nu/\nu'\right)$ where ζ is the trade elasticity and ν and ν' denote the share of aggregate spending on domestic goods before and after the change of trade cost. Following the literature, we calculate trade elasticity by $d\ln\left(\frac{1-\nu}{\nu}\right)/d\ln\tau$. We simulate trade elasticities local to our benchmark estimates for 1995 and 2004, and they are -2.49 and -1.28, respectively. Using the trade elasticity implied by our 2004 model, the gains from trade between 1995 and 2004 according to ACR's formula are 11.6%, whereas the gains calculated with the trade elasticity implied by our 1995 model are 5.9%. The (total) gains from trade in this period based on our 2004 and 1995 model are 9.4% and 7.8% (see Table 7), respectively, and these numbers are in the ballpark of the ACR statistics.

The overall gains from trade are substantially larger in our model compared with typical results in the literature. As highlighted by ACR, trade elasticities are crucial in determining the magnitude of welfare gains. Hence, this result is not surprising, as the trade elasticities here are smaller due to smaller values of σ. As discussed in Section 3.3, the elasticity of substitution inversely determines the upper bound of markups, rather than the average markup. Thus, the larger welfare gains in our quantitative analyses are fundamentally a direct consequence of accommodating the empirical markup dispersion in the BEJK oligopoly environment, which differs drastically from constant-markup models, whether they are perfectly or monopolistically competitive.

4.2 Symmetric Countries

For the purposes of comparison, we also estimate a symmetric-country case. The estimation results are shown in Table 5 and the counter-factual results in Table 6. The changes in trade cost τ, measure of goods γ and number of firms per product λ between 1995 and 2004 are all in the same direction as in the benchmark case. Note that the estimated λ is similar to a weighted average of estimated λ_1 and λ_2, with the ROW weighted more heavily, since the ROW is much larger than China. Also, observe that although the standard errors here are somewhat smaller than those in the benchmark estimation, the fit of moments becomes significantly worse. This is because there are fewer parameters in the symmetric-country estimation, reflecting that the symmetric-country estimation misses out the large discrepancy in entry and productivity distribution seen in Table 2. It may also be partly because symmetric-country model misses out the general equilibrium effect in the adjustment of relative wages, which change from 10.5 to 5.3 (See Table 2), meaning that Chinese wages relative to the ROW almost doubled in this decade.

For counter-factual results, first note that the markup level effect does not show up in Table 6 because this term drops out under symmetric countries. Also, note that the overall welfare gains become much smaller than the benchmark case (e.g. 2.7% versus 9.4%). Both components also become much smaller. As the distributions of the number of entrants and productivity draws become the same between the two countries, the Ricardian gains are reduced because active firms' productivity differences between two countries are now reduced. Moreover, not only do the distribution of markups become similar, but the dispersion of markups also becomes smaller. In fact, looking at the autarky, we see that the allocative efficiency is much larger in the symmetric-country case than in the benchmark case (0.941 versus 0.898). As the allocative efficiency is larger to start with, it is not surprising that the gains in allocative efficiency are smaller (0.7% versus 2.1% and 2.5% versus 7.5%). The same rationale explains why we see a pronounced diminishing-returns (dropping from 32.5% to 13.3%) pattern in Panel B that is absent in the asymmetric-country case.

Under symmetric countries, the results in Edmond et al. rely on the cross-country productivity differences across different sectors to generate pro-competitive effects. However, our exercise indicates that asymmetries between countries could also be important sources of gains, both in Ricardian component and the pro-competitive effects. Nevertheless, the relative contributions of the pro-competitive effects are still somewhat close to those at the benchmark case, albeit the variation is somewhat larger.

4.3 Robustness

We conduct three robustness checks. Recall that in the benchmark case, the counter-factual analyses are based on 2004 estimates and change τ back to the 1995 level. In our first robustness check, we conduct a counter-factual analysis based on 1995 estimates and change τ to the 2004 level. In our second check, we use an alternative measure of markups to estimate the model and run counter-factuals. That is, by invoking the constant-returns-to-scale assumption, we calculate *raw markups* by taking the ratio of revenue to total costs. For our third check, recall that we used the 99th percentile of the markup distribution to infer σ, but now we also report results based on the 97.5th percentile.

The results are reported in Table 7. The relative contribution of pro-competitive effects ranges from 19.4% to 24.0%, and that of allocative efficiency ranges from 19.3% to 22.4%. These indicate that the benchmark results are quite robust, as the importance of allocative efficiency remains similar, and the markup level effect remains small.

The only difference between the first robustness check and the benchmark is that all parameters besides τ are fixed at the 1995 levels instead of at the 2004 levels. Both the overall gains and the pro-competitive effects are smaller in the first robustness check than in the benchmark. As China had smaller productivity and smaller entry in 1995, this indicates a complementary effect between trade liberalization and other fundamentals in the sense that there are more gains from trade when productivity and entry are higher.

Next, note that the σ inferred from raw markups is about 1.67, which implies a smaller upper bound of markups than the benchmark case. So it is not surprising that the pro-competitive effects are slightly less important under raw markups. This also explains why using the 97.5th percentile of the markup distribution to infer σ also induces smaller pro-competitive effects.

4.4 Gains from Tariff Reductions

Following the literature, the iceberg trade cost can be represented as $\tau = (1+t) \times \tau^{\text{non-tariff}}$, where t denotes economy-wide average tariff.[21] Equivalently, we can write

$$\ln \tau = \ln (1+t) + \ln \tau^{\text{non-tariff}}.$$

The average import and export tariffs are 25.5% and 6.4% respectively in 1995, and the weighted average is 15.7%. (For details of the calculation, see Appendix A2). The corresponding numbers in 2004 are 6.3%, 3.2% and 4.3%. When China experienced sizable decrease in the export tariff of about 50%, the drop in the import tariff was much larger. The large drop in the average tariff from 15.7% to 4.3% is evidence of the power of the WTO entry. Using our benchmark estimate of τ, 2.311 and 1.664 in 1995 and 2004, respectively, the corresponding $\tau^{\text{non-tariff}}$ are 1.997 and 1.595. This means that the decrease in tariffs accounts for $\Delta \ln (1+t) / \Delta \ln \tau = 31.6\%$ of the decrease in overall trade friction. Although this is not a small magnitude, it indicates that the decrease in non-tariff trade friction is even more important.

Next, we conduct two counter-factual exercises to single out the effect of tariffs, and the results are shown in Table 8. Panel A shows the result based on the 2004 estimates. That is, based on 2004 estimates, we keep $\tau^{\text{non-tariff}}$ at the 2004 level, and consider the effect of tariffs. Hence, τ changes from 1.845 in 1995 to 1.664 in 2004. Then, we compare this effect with the overall effect when $\tau^{\text{non-tariff}}$ is also allowed to change. Panel B reports the results based on 1995 estimates, and hence τ changes from 2.311 in 1995 to 2.083 in 2004 when $\tau^{\text{non-tariff}}$ is kept at the 1995 level.

When $\tau^{\text{non-tariff}}$ is kept at the 2004 level, the reduction in tariffs from 1995 to 2004 brings 3.7% total welfare gains, with the pro-competitive effects accounting for about 20.3% of these gains. But when $\tau^{\text{non-tariff}}$ is allowed to change, the total gains increase to 9.4% and the pro-competitive effects contribute about 25.4%. The relative contribution of the tariff reduction is 39.6%. The difference in the relative contribution of the pro-competitive effects is consistent with the findings of "diminishing returns" as reported in Panel B of Table 4 and discussed in Section 4.1.

The key difference between Panels A and B in Table 8 is the magnitudes of $\tau^{\text{non-tariff}}$. In 1995, $\tau^{\text{non-tariff}} = 1.997$ is relatively large, and a 31.6% decrease in overall trade friction due to tariffs accounts for 35.2% of the total welfare gains. In contrast, in 2004, $\tau^{\text{non-tariff}} = 1.595$ is relatively small, and a 31.6% decrease of overall trade friction due to tariffs accounts for 39.6% of the total welfare gains. In other words, the same proportional change in trade

[21] For example, see Caliendo and Parro (2015).

friction due to tariff reductions entails larger gains when the non-tariff trade friction is lower.

5 Multiple-Sector Economy

The framework in this paper can be easily extended to a multiple-sector economy, which we do for three reasons. First, the model is more realistically matched to data, taking into account the cross-sector heterogeneity in trade costs, as well as in productivity distribution, entry effort and preference parameters. Second, we conduct similar welfare analyses to gauge the robustness of our previous results for this multiple-sector extension. Third, exploiting the variations in sectoral markups and trade costs, we attempt to answer the question of whether China trade-liberalized the "right" sectors by examining whether there was larger trade liberalization in sectors with higher initial markups in 1995.

5.1 Model and Estimation

Model Modification There are S sectors, which are indexed by $s = 1, 2, ..., S$. The utility function of a representative consumer is

$$U = \Pi_{s=1}^{S} \left(Q_s\right)^{\alpha_s},$$

where $\alpha_s \in (0, 1)$, $\sum_{s=1}^{S} \alpha_s = 1$, and Q_s is the consumption of the composite good of sector s given by a CES aggregator:

$$Q_s = \left(\int_0^{\bar{\omega}_s} \left(q_{s,\omega}\right)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right)^{\frac{\sigma_s}{\sigma_s - 1}}, \text{ for } \sigma_s > 1,$$

where σ_s is the elasticity of substitution of sector s. The aggregate and sectoral price indices are therefore

$$\begin{aligned} P_j &= \Pi_{s=1}^{S} \left(\frac{P_{js}}{\alpha_s} \right)^{\alpha_s} \\ P_{js} &\equiv \left(\int_0^{\bar{\omega}_s} p_{js\omega}^{1-\sigma_s} d\omega \right)^{\frac{1}{1-\sigma_s}}. \end{aligned}$$

The Cobb-Douglas structure implies that $P_{js} Q_{js} = \alpha_s R_j$, and country j's total expenditure of good $s\omega$ is given by

$$E_{js\omega} = \alpha_s R_j \left(\frac{p_{js\omega}}{P_{js}} \right)^{1-\sigma_s} \equiv \alpha_s R_j \phi_{js\omega},$$

and the total revenue of all firms at i in sector s is

$$R_{s,i} = \int_{\left\{s\omega:\ \chi_1^*(s\omega)=i\right\}} \alpha_s R_1 \phi_{1s\omega} d\omega + \int_{\left\{s\omega:\ \chi_2^*(s\omega)=i\right\}} \alpha_s R_2 \phi_{2s\omega} d\omega$$

For each sector s, all the parameters in the one-sector economy now become sector-specific. That is, for each sector s there is a τ_s and a γ_s, and for sector s and country i, there is a set $\{\lambda_{is}, \mu_{is}, \eta_{is}\}$. For each sector, pricing and markups follow the previous formulation.

Wages and General Equilibrium The labor demand for a non-exporter at i that produces good $s\omega$ is

$$\ell_{s\omega,i} = \frac{q_{is\omega}}{\varphi^*_{s\omega,i}} = \frac{1}{\varphi^*_{s\omega,i}} \frac{\alpha_s R_i}{P_{is}} \left(\frac{p_{is\omega}}{P_{is}}\right)^{-\sigma_s}.$$

The labor demand for an exporter at $i = 1$ or 2 is

$$\begin{aligned}
\ell_{s\omega,1} &= \frac{q_{1s\omega} + \tau q_{2s\omega}}{\varphi^*_{s\omega,1}} = \frac{1}{\varphi^*_{s\omega,1}} \left[\frac{\alpha_s R_1}{P_{1s}} \left(\frac{p_{1s\omega}}{P_{1s}}\right)^{-\sigma_s} + \frac{\tau_s \alpha_s R_2}{P_{2s}} \left(\frac{p_{2s\omega}}{P_{2s}}\right)^{-\sigma_s}\right], \\
\ell_{s\omega,2} &= \frac{\tau_s q_{1s\omega} + q_{2s\omega}}{\varphi^*_{s\omega,2}} = \frac{1}{\varphi^*_{s\omega,2}} \left[\frac{\tau_s \alpha_s R_1}{P_{1s}} \left(\frac{p_{1s\omega}}{P_{1s}}\right)^{-\sigma_s} + \frac{\alpha_s R_2}{P_{2s}} \left(\frac{p_{2s\omega}}{P_{2s}}\right)^{-\sigma_s}\right].
\end{aligned}$$

Labor market clearing in country i is

$$\sum_{s=1}^{S} \int_{\omega \in \chi_{s,i}} \ell_{s\omega,i} d\omega = L_i,$$

where $\chi_{s,i}$ is the set of $s\omega$ produced at i.

For trade flows, observe that country j's total import from country i is

$$R_{j,i} = \sum_{s=1}^{S} \int_{\left\{s\omega:\ \chi_j^*(s\omega)=i\right\}} E_{js\omega} d\omega = R_j \phi_{j,i}$$

where $\chi_j^*(s\omega) \in \{1,2\}$ denotes the source country for any particular good $s\omega$ at destination j and $\phi_{j,i}$ is the total spending share of j on i's goods:

$$\phi_{j,i} = \sum_{s=1}^{S} \alpha_s \int_{\left\{s\omega:\ \chi_j^*(s\omega)=i\right\}} \phi_{js\omega} d\omega. \tag{6}$$

The balanced trade condition $R_{2,1} = R_{1,2}$ holds in equilibrium.

Welfare The welfare of country i is decomposed in the same way as before

$$W_i^{Total} = w_i L_i \times \frac{1}{A_i} \times \frac{M_i^{sell}}{M_i^{buy}} \times \frac{A_i \times M_i^{buy}}{P_i},$$

where

$$\begin{aligned} A_i &= \Pi_{s=1}^{S} \left(\frac{A_{is}}{\alpha_s}\right)^{\alpha_s}, & P_i = \Pi_{s=1}^{S} \left(\frac{P_{is}}{\alpha_s}\right)^{\alpha_s}, \\ M_i^{buy} &= \left(\sum_{s=1}^{S} \alpha_s \left(M_{is}^{buy}\right)^{-1}\right)^{-1}, & M_i^{sell} = \frac{R_i}{w_i L_i} = \left(\sum_{s=1}^{S} \frac{R_{s,i}}{R_i} \left(M_{is}^{sell}\right)^{-1}\right)^{-1}, \end{aligned} \quad (7)$$

and A_{is}, P_{is}, and M_{is}^{buy} are defined in the same way as before, and M_{is}^{sell} is

$$M_{is}^{sell} = \left(\int_{\{\omega:\, \chi_{s1}^*(\omega)=i\}} m_{1s\omega}^{-1} \frac{\alpha_s R_1 \phi_{1s\omega}}{R_{s,i}} d\omega + \int_{\{\omega:\, \chi_{s2}^*(\omega)=i\}} m_{2s\omega}^{-1} \frac{\alpha_s R_2 \phi_{2s\omega}}{R_{s,i}} d\omega\right)^{-1}. \quad (8)$$

The sectoral welfare cannot be further decomposed into the three components as in the one-sector model. This breaks down because there is no simple analogue of $R_i = w_i L_i \times M_i^{sell}$ at the sectoral level. Indeed, $w_i L_i = \sum_s \frac{R_{is}}{M_{is}^{sell}}$.

Quantifying the Model To quantify the model, we focus on 29 2-digit manufacturing sectors in Chinese Industrial Classifications (CIC).[22] We first calibrate $\{\alpha_s\}_{s=1}^{S}$. Recall that $P_{1s}Q_{1s} = \alpha_s R_1$. We use information about expenditure share in China's 1997 and 2002 input-output table to calibrate α_{st}, where $t = 1997, 2002$. We then set α_s to be the average between two years.[23] We then follow the same procedure as in the one-sector economy case to infer the elasticity of substitution σ_s and estimate the remaining parameters by SMM using sectoral firm-level data. Note that one convenience in our framework is that to implement SMM, moments are generated given wages w and total revenue R_1 and R_2, and each sector is actually estimated separately, which largely simplifies the estimation and equilibrium computation for counter-factuals.

The parameter estimates are shown in Tables 9A and 9B. In both tables, we also report the (unweighted) mean, standard deviation, maximum and minimum of the estimates and percentage changes across sectors. There are substantial variations across industries in their

[22] We include all 2-digit CIC manufacturing sectors except Sector 43 because we do not have the necessary data to calculate markups for this industry.

[23] Specifically, we first map the input-output code to 2-digit CIC sectors. Then, we calculate the expenditure share for each 2-digit CIC sector, where the expenditure is calculated by subtracting exports from total use, which already includes imports.

moments. The model performs well in accommodating these variations with corresponding variations in the estimates. The changes in the unweighted means of parameters between 1995 and 2004 are all consistent with the pattern observed in the one-sector case, except for the parameter η_1 (see Table 2). In particular, all estimated trade costs decrease except for Tobacco Processing.[24] Also observe that the mean σ_s is 1.44, which is quite close to our benchmark in the one-sector economy, and σ_s in most industries (23 out of 29) are within one standard deviation from the mean, $(1.27, 1.61)$.

5.2 Gains from Trade

When examining the welfare analysis in the multi-sector economy, we focus on the two key counter-factuals shown in Table 10. In this table, Panel A is similar to Panel A in Table 4 (the benchmark in the one-sector economy). Whereas we changed τ in the one-sector economy, we now change $\{\tau_s\}$ for all sectors s from the 2004 values to the 1995 values (or to inhibitive values). The relative contribution of pro-competitive effects here is around 20%, which is slightly smaller than the numbers in Table 4. Similarly, allocative efficiency accounts for almost all of the pro-competitive effects. Panel B shows the effect of tariff reductions, while fixing non-tariff trade costs $\left\{\tau_s^{\text{non-tariff}}\right\}$ at 2004 levels. Note that the column of "% change (from trade costs in 1995)" is copied from Panel A. The relative contribution of tariff reductions accounts 34.8% of the total welfare gains. This is slightly lower than the number (39.6%) in Table 8 and remains larger than the proportion of average tariff reductions in the overall reduction in trade costs (31.6%, see Section 4.4). In sum, the results of welfare gains are similar to those in the one-sector economy case.

5.3 Did China Trade-Liberalized the Right Sectors?

In this subsection, we try to answer the question of whether China trade-liberalized the right sectors? We examine the relationship between trade liberalization and sectoral consumers' aggregate markup (M_{1s}^{buy}) under the 1995 model. That is, if a sector has a higher M_{1s}^{buy} in 1995, do we also actually see a larger degree of trade liberalization between 1995 and 2004? The rationale is as follows. Recall from (7) that aggregate markup M_1^{buy} is a harmonic mean of sectoral markups (M_{1s}^{buy}). From both one-sector and multi-sector welfare analysis, we observe that most pro-competitive gains from trade are due to allocative efficiency. As the overall allocative efficiency depends on the dispersion of markups across sectors, if a sector s has higher M_{1s}^{buy} initially, then allocative efficiency will improve more if the government

[24] This is mainly because the import and export shares decrease from 0.021 and 0.052 to 0.010 and 0.016 in this sector.

targets its trade liberalization more in these higher markup sectors.

A quick examination is to rank the 29 sectors by their values of M_{1s}^{buy} at 1995 and divide them into two groups – the first being 15 sectors with the smaller values of M_{1s}^{buy} and the second being those with the larger values. The weighted average of the M_{1s}^{buy} are then 1.21 and 1.36, respectively. The corresponding weighted average of the changes in trade costs τ_s (i.e, $\Delta\tau_s = \tau_{s,2004} - \tau_{s,1995}$) are -0.446 and -0.856, respectively. An alternative measure of trade liberalization is the changes in sectoral import tariffs,[25] which directly relate to the WTO entry but do not account for other factors of trade liberalization. In this case, the corresponding changes are -0.162 and -0.215, respectively. These simple statistics show a tendency where the higher the initial level of sectoral markups, the larger the reduction in trade costs (or import tariffs).

Columns 1 and 5 of Table 11 show similar results by regressing the changes in sectoral trade costs and in sectoral import tariffs on sectoral markups M_{1s}^{buy} at 1995.[26] Note that these descriptive results suffice for our purpose, as we only want to examine whether China on average trade-liberalized the right sectors, smoothing the dispersion of markups across sectors, even if this happened by chance. In other words, we do not try to establish causality. Nevertheless, we also examine conditional correlations by following Trefler (2004) in accounting for factors that may affect the changes in tariffs. Columns 3 and 7 show the results when we add controls for log of wage rates, employment, exports, and imports, all at 1995. The rationale of these controls is that they are highly correlated with various kinds of protectionism.[27] As the share of SOEs is presumably a good indicator of protectionism in China, we also add this as a control (see columns 2, 4, 6, and 8). The above-mentioned tendency still remains.[28]

One often-mentioned merit of trade liberalization (or tariff reduction) is that it is an easier route to reducing domestic protectionism compared with using domestic industrial policies. Before joining the WTO, import tariffs varied greatly in China, but the WTO conditions generally require larger tariff reductions in those industries with higher initial tariffs (see Lu and Yu 2015). We do not know whether the Chinese government had benevolent motives and wanted to enhance welfare; it could simply be a mechanical result of China wanting to enter the WTO. Anyway, our structural approach allows a welfare assessment in the context of sectoral reallocation both in terms of improved overall allocative efficiency (Table 10) and

[25] For details of how the sectoral import tariffs are calculated, see Appendix A2.

[26] As sector-level data is grouped data from either firms or products, we weight the regressions by trade volume and imports when the dependent variables are changes in trade cost and import tariffs, respectively.

[27] For a detailed explanation, see Trefler (2004), p. 878.

[28] All the coefficients on sectoral markup at 1995 are significant except in column 4, which is marginally insignificant (with a p-value at 0.11). Nevertheless, the value of this coefficient is similar to those in columns 1-3. Also, as the sample size is small (29), one should use caution when interpreting the significance levels.

the results in this subsection.

6 Conclusion

Using Chinese trade data and firm-level data at 1995 and 2004, this paper studies pro-competitive effects of trade quantitatively under an oligopoly model with finite numbers of firms for each product. The benchmark counter-factual shows that pro-competitive effects account for 25.4% of the total gains from trade from 1995 to 2004 and 23.3% from autarky to 2004. Allocative efficiency plays a much more important role than the markup level effect. These benchmark quantitative magnitudes of pro-competitive effects are robust to a variety of robustness checks, ranging from 19.4% to 25.4% of total gains from trade from 1995 to 2004 and from 19.6% to 31.4% of those gains from autarky to 2004 (Tables 4, 6 and 7).

When comparing with the symmetric-country case, we find that the gains from trade and its components are substantially smaller in the symmetric-country case, indicating the important role played by the differences in productivities and markups. As the distributions of the number of entrants and productivity draws become the same between the two countries, the Ricardian gains are reduced because active firms' productivity differences between two countries are now reduced. Moreover, not only do the distribution of markups become similar, but the dispersion of markups also becomes smaller. Taking advantage of the tariff data, we also find that tariff reductions account for about 32% of reductions in overall trade costs, whereas the associated relative contribution to overall gains is slightly larger at 39.6%. This provides the lower bound of the effects attributable to the WTO entry.

The welfare results remain similar in the multi-sector economy, with the relative contribution of the pro-competitive effects and tariff reductions around 20% and 35%, respectively. Exploiting the variations in sectoral markups and trade costs, we find that China on average trade-liberalized the "right" sectors in the sense that the dispersion of markups is reduced because there tended to be larger trade liberalization in sectors with higher initial markups. Even though we do not know exactly how this happened, to target trade liberalization in sectors with higher markups is a useful take away. This is particularly so when it is difficult to eliminate distortions in some industries via domestic measures.

Appendix

A1. Algorithm of Computing Equilibrium

We describe a procedure that reduces three equilibrium conditions in three unknowns $\{w, R_1, R_2\}$ to one equation in one unknown w. This is useful for faster computation.

One-Sector Economy First, observe from the definition of the producers' aggregate markup for country 1:

$$\begin{aligned} M_1^{sell} &= \frac{R_1}{w_1 L_1} = \left(\int_{\{\omega:\ \chi_1^*(\omega)=1\}} m_{1\omega}^{-1} \phi_{1\omega} d\omega + \int_{\{\omega:\ \chi_2^*(\omega)=1\}} m_{2\omega}^{-1} \phi_{2\omega} \frac{R_2}{R_1} d\omega \right)^{-1} \\ &= \left(\int_{\{\omega:\ \chi_1^*(\omega)=1\}} m_{1\omega}^{-1} \phi_{1\omega} d\omega + \int_{\{\omega:\ \chi_2^*(\omega)=1\}} m_{2\omega}^{-1} \phi_{2\omega} \frac{\phi_{1,2}}{\phi_{2,1}} d\omega \right)^{-1}, \end{aligned}$$

in which the second line uses the balanced trade condition $\frac{R_2}{R_1} = \frac{\phi_{1,2}}{\phi_{2,1}}$, where $\phi_{j,i}$ denote the total spending share of country j's consumers on good from country i. Note that $\phi_{j,i} = \int_{\{\omega:\ \chi_j^*(\omega)=i\}} \phi_{j\omega} d\omega$ only depends on relative wage w, but not on R_1 and R_2. Hence, M_1^{sell} becomes a function of w only. For any given w, we can calculate $M_1^{sell}(w)$. Then, given $w_1 = 1$ and L_1, we get $R_1(w) = M_1^{sell}(w) L_1$. For R_2, we use the balanced trade condition again:

$$R_2(w) = \frac{\phi_{1,2}}{\phi_{2,1}}(w) \times R_1(w).$$

In fact, $M_i^{sell} = \frac{R_i}{w_i L_i}$ is equivalent to the labor market clearing condition of country i. Next, we calculate

$$M_2^{sell}(w) = \left(\int_{\{\omega:\ \chi_1^*(\omega)=i\}} m_{\omega,1}^{-1} \phi_{\omega,1} \frac{\phi_{2,1}}{\phi_{1,2}}(w) d\omega + \int_{\{\omega:\ \chi_2^*(\omega)=i\}} m_{\omega,2}^{-1} \phi_{\omega,2} d\omega \right)^{-1}.$$

Finally, given L_2, we can use the market clearing condition of country 2 to solve for w:

$$M_2^{sell}(w) = \frac{R_2(w)}{w L_2}.$$

Given the solution of w, we obtain R_1 and R_2 via the $R_i(w)$ formula above.

Multiple-Sector Economy The algorithm for calculating an equilibrium in a multiple-sector economy is similar. From (7) and (8), we can derive the following formula of M_1^{sell}

and M_2^{sell}:

$$M_1^{sell} = \left[\sum_{s=1}^{S} \alpha_s \left(\int_{\{\omega:\, \chi_{s1}^*(\omega)=1\}} m_{1s\omega}^{-1}\phi_{1s\omega} d\omega + \int_{\{\omega:\, \chi_{s2}^*(\omega)=1\}} m_{2s\omega}^{-1}\phi_{2s\omega}\frac{\phi_{1,2}}{\phi_{2,1}} d\omega\right)\right]^{-1}$$

$$M_2^{sell}(w) = \left[\sum_{s=1}^{S} \alpha_s \left(\int_{\{\omega:\, \chi_{s1}^*(\omega)=2\}} m_{1s\omega}^{-1}\phi_{1s\omega}\frac{\phi_{2,1}}{\phi_{1,2}}(w)\, d\omega + \int_{\{\omega:\, \chi_{s2}^*(\omega)=2\}} m_{2s\omega}^{-1}\phi_{2s\omega} d\omega\right)\right]^{-1},$$

in which $\phi_{j,i}$ is the total spending share of j on i's goods given in (6). Then, we still calculate $R_1(w) = M_1^{sell}(w)\, L_1$, $R_2(w) = \frac{\phi_{1,2}}{\phi_{2,1}}(w) \times R_1(w)$, and $M_2^{sell}(w) = \frac{R_2(w)}{wL_2}$, and the last is used to pin down equilibrium wage ratio w.

A2. Calculation of Average Tariffs

There are two data sources for tariffs in World Integrated Trade Solution (WITS): TRAINS and WTO-IDB (WTO's Integrated Data Base). We use TRAINS as it covers more countries and more years. An observation of tariff is an average tariff at HS 6-digit product level, and it is specific to a pair of importing and exporting countries. We extract data from WITS when China is involved as either an importing or exporting country and use "effectively applied rates" (AHS).[29] The reported tariffs are already averages of finer HS lines. Nevertheless, the reported "Simple Average" at HS 6-digit level is essentially equal to the reported "Weighted Average".[30] But, since there are more missing values in "Weighted Average", we opt to use "Simple Average". Note that WITS does not report China's import tariffs in 1995, and so we take averages of the 1994 and 1996 tariffs as proxies.

In calculating sectoral average tariffs, we use the mapping of HS 6-digit to CIC 2-digit manufacturing sectors using the concordance table from the National Bureau of Statistics of China.[31] We then use trade values (exports or imports in the corresponding product or industry) from the previous year (1994 and 2003) as weights to calculate average tariffs.[32]

[29] Another duty type that is also reported is MFN (most favored nation). Although there may be sizable differences between the two, but the number of observations that they differ is small. For example, for export tariffs, these numbers are 6914 and 8950, or about 12% and 4% of the samples, for 1995 and 2004, respectively.

[30] For example, in the 1995 and 2004 export tariff data, the maximum absolute difference between the two averages is 0.01 percentage point, and they differ merely in 4 and 33 observations in 1995 and 2004, respectively.

[31] We thank Yifan Zhang for sharing this concordance table. Note that this table is based on HS2002. Hence, whenever HS1992 and HS1996 are used in the tariff data, we map them to HS2002 using the concordance tables available from WITS. See http://wits.worldbank.org/product_concordance.html.

[32] We slightly prefer using previous-year trade values as weight because if there is any change in tariffs, there may be some induced changes in trade values, making the average tariff using current-year trade values "less exogenous". Note that these trade values actually come from UN COMTRADE, and so whenever what is provided by the WITS is less complete, we use the ones from UN COMTRADE.

Similarly, to calculate an economy-wide tariff, we again take a weighted average of tariffs across all sectors and between imports and exports.

A3. Estimation of Markups

In this subsection, we provide the details for calculating firm markups using DLW's method. Specifically, we assume that firm i at time t has the following production technology[33]

$$Q_{it} = F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right), \tag{9}$$

where L_{it}, K_{it}, and M_{it} are the inputs of labor, capital and intermediate materials, respectively; ω_{it} denotes firm-specific productivity. The production function $F(.)$ is assumed to be continuous and twice-differentiable with respect to all of its arguments.

Consider the following cost minimization problem firm i faces at time t

$$\min_{\{L_{it}, K_{it}, M_{it}\}} w_{it}L_{it} + r_{it}K_{it} + p_{it}^{m}M_{it} \tag{10}$$

$$s.t.\ F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right) \geq Q_{it},$$

where w_{it}, r_{it}, and p_{it}^{m} denote the wage rate, rental price of capital and the price of intermediate inputs, respectively; and Q_{it} is a given number of output.

The estimation of firm-level markup hinges on choosing an input that is free of any adjustment costs, and the estimation of its output elasticity. As labor is largely not freely chosen in China (particularly state-owned enterprises) and capital is often considered a dynamic input (which makes its output elasticity difficult to interpret), we choose intermediate materials as the input to estimate firm markup (see also DLW). Specifically, the Lagrangian function associated with the optimization problem (10) can be written as

$$\begin{aligned}\mathcal{L}\left(L_{it}, K_{it}, M_{it}, \lambda_{it}, \eta_{it}\right) \quad = \quad & w_{it}L_{it} + r_{it}K_{it} + p_{it}^{m}M_{it} \\ & + \lambda_{it}\left[Q_{it} - F_{it}\left(L_{it}, K_{it}, M_{it}, \omega_{it}\right)\right].\end{aligned}$$

Hence, the first-order condition for intermediate materials is

$$\frac{\partial \mathcal{L}}{\partial M_{it}} = p_{it}^{m} - \lambda_{it}\frac{\partial F_{it}}{\partial M_{it}} = 0. \tag{11}$$

[33] Note that the framework is robust to any arbitrary number of inputs. As we only observe three inputs (i.e., labor, capital and intermediate materials) in our data, here we focus on production technology involving only these three inputs.

Rearranging equation (11) and multiplying both sides by $\frac{M_{it}}{Q_{it}}$ yield

$$\begin{aligned} \frac{\partial F_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}} &= \frac{1}{\lambda_{it}} \frac{p_{it}^m M_{it}}{Q_{it}} \\ &= \frac{P_{it}}{\lambda_{it}} \frac{p_{it}^m M_{it}}{P_{it} Q_{it}}, \end{aligned} \tag{12}$$

where P_{it} is the price of the final good.

Note that $\lambda_{it} = \frac{\partial \mathcal{L}}{\partial Q_{it}} = mc_{it}$ represents the marginal cost of production at a given level of output. Define firm markup μ_{it} as the ratio of price over marginal cost, i.e. $\mu_{it} \equiv \frac{P_{it}}{mc_{it}} = \frac{P_{it}}{\lambda_{it}}$. Hence, equation (12) leads to the following estimation expression of firm markup[34]

$$\mu_{it} = \theta_{it}^m \left(\alpha_{it}^m\right)^{-1}, \tag{13}$$

where $\theta_{it}^m \equiv \frac{\partial F_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}}$ is the output elasticity of intermediate materials and $\alpha_{it}^m \equiv \frac{p_{it}^m M_{it}}{P_{it} Q_{it}}$ is the share of the expenditure of intermediate materials in total revenue.

As the information about the expenditure on intermediate materials and total revenue is available in the data, α_{it}^m can be readily calculated. However, the output elasticity of intermediate materials, θ_{it}^m, needs to be obtained through estimating the production function (9). There is a large literature on the estimation of the production function focusing on how to control for unobserved productivity shocks (for a review, see Ackerberg, Benkard, Berry and Pakes 2007). The solutions range from the instrumental variable estimation to the GMM estimation, and to the control function approach proposed by Olley and Pakes (1996). We adopt the control function approach developed by Ackerberg, Caves and Frazier (2006), which comprises a two-step estimation.

Similar to DLW, we assume a translog production function when estimating markups. Specifically, the production function to be estimated is expressed as

$$\begin{aligned} q_{it} = \; & \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ & + \beta_{lk} l_{it} k_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} \\ & + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}, \end{aligned} \tag{14}$$

where the lowercase letters represent the logarithm of the uppercase letters; ω_{it} is firm-specific productivity; and ε_{it} is an *i.i.d.* error term. $\boldsymbol{\beta}= (\beta_l, \beta_k, \beta_m, \beta_{ll}, \beta_{kk}, \beta_{mm}, \beta_{lk}, \beta_{km}, \beta_{lm}, \beta_{lkm})$

[34] Note that this expression holds under any form of market competition and demand function. Specifically, DLW discuss some alternative market structures, which lead to a similar estimation expression for firm markup. These alternative market structures include Cournot competition, Bertrand competition, and monopolistic competition.

is the vector of production function coefficients.

To proxy ω_{it}, Levinsohn and Petrin (2003) assume that

$$m_{it} = m_t\left(k_{it}, \omega_{it}, ex_{it}\right),$$

where ex_{it} denotes the exporter status (i.e. taking value 1 if exporters and 0 otherwise). Given the monotonicity of $m_t(.)$, we can have

$$\omega_{it} = h_t\left(m_{it}, k_{it}, ex_{it}\right).$$

In the first stage, we estimate the following equation

$$q_{it} = \phi_{it} + \varepsilon_{it},$$

where

$$\begin{aligned}\phi_{it} &= \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ &\quad + \beta_{lk} l_{it} k_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + h_t\left(m_{it}, k_{it}, ex_{it}\right),\end{aligned}$$

and obtain the estimates of the expected output ($\hat{\phi}_{it}$) and the error term ($\hat{\varepsilon}_{it}$).

Meanwhile, to recover all the production function coefficients $\boldsymbol{\beta}$ in the second stage, we model that firm productivity follows a first-order Markov movement, i.e.

$$\omega_{it} = g_t\left(\omega_{it-1}\right) + \xi_{it},$$

where ξ_{it} is an idiosyncratic shock.

From the first stage, the productivity for any given value of $\boldsymbol{\beta}$ can be computed as

$$\omega_{it}\left(\boldsymbol{\beta}\right) = \hat{\phi}_{it} - \left(\begin{array}{c} \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ + \beta_{lk} l_{it} k_{it} + \beta_{km} k_{it} m_{it} + \beta_{lm} l_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} \end{array}\right).$$

The idiosyncratic shock to productivity given $\boldsymbol{\beta}$, $\xi_{it}\left(\boldsymbol{\beta}\right)$, can then be obtained through a non-parametric regression of $\omega_{it}\left(\boldsymbol{\beta}\right)$ on $\omega_{it-1}\left(\boldsymbol{\beta}\right)$.

To identify the coefficients of the production function, Ackerberg, Caves and Frazier (2006) assume that capital is determined one period beforehand and hence is not correlated with $\xi_{it}\left(\boldsymbol{\beta}\right)$. Meanwhile, wage rates and prices of intermediate materials are assumed to vary across firms and be serially correlated.

Therefore, the moment conditions used to estimate the coefficients of the production function are

$$E\left(\xi_{it}\left(\boldsymbol{\beta}\right)\mathbf{Y}'_{it}\right)=0,$$

where $\mathbf{Y}_{it}=\{l_{it-1},l_{it-1}^2,m_{it-1},m_{it-1}^2,k_{it},k_{it}^2,l_{it-1}m_{it-1},l_{it-1}k_{it},m_{it-1}k_{it},l_{it-1}m_{it-1}k_{it}\}$.

We estimate the translog production function (14) separately for each 2-digit industry using the Annual Survey of Manufacturing Firms conducted by the NBS from 1998 to 2005. Specifically, we use the logarithm of sales deflated by 2-digit ex-factory price indices to measure q_{it}, the logarithm of employment to measure l_{it}, the logarithm of the net value of fixed assets deflated by investment price indices to measure k_{it}, and the logarithm of intermediate materials[35] deflated by input price indices to measure m_{it}; both price indices are provided by Brandt, Van Biesebroeck and Zhang (2012).

Once $\hat{\boldsymbol{\beta}}=\left(\hat{\beta}_l,\hat{\beta}_k,\hat{\beta}_m,\hat{\beta}_{ll},\hat{\beta}_{kk},\hat{\beta}_{mm},\hat{\beta}_{lk},\hat{\beta}_{km},\hat{\beta}_{lm},\hat{\beta}_{lkm}\right)$ is obtained, we can readily calculate the firm markup using equation (13), i.e.

$$\hat{\mu}_{it}=\hat{\theta}_{it}^{m}\left(\alpha_{it}^{m}\right)^{-1},$$

where $\hat{\theta}_{it}^{m}=\hat{\beta}_m+2\hat{\beta}_{mm}m_{it}+\hat{\beta}_{lm}l_{it}+\hat{\beta}_{km}k_{it}+\hat{\beta}_{lmk}l_{it}k_{it}$. Production estimates are reported in Table A1.

[35] We calculate the value of intermediate materials as total production costs-current year depreciation*production costs/(production costs+selling costs+administrative costs+financial costs)-total wages-total welfare benefits.

References

Ackerberg, D., C. L. Benkard, S. Berry, and A. Pakes (2007), "Econometric Tools for Analyzing Market Outcomes" in *Handbook of Econometrics*, Volume 6A, ed. James J. Heckman and Edward E. Leamer, 4171–276. Amsterdam and Boston: Elsevier, North-Holland.

Ackerberg, D., K. Caves, and G. Frazer (2006), "Structural Identification of Production Functions", working paper, UCLA.

Arkolakis, C., A. Costinot, and A. Rodriguez-Clare (2012), "New Trade Models, Same Old Gains?," *American Economic Review*, 102(1): 94–130.

Arkolakis, C., A. Costinot, D. Donaldson, and A. Rodriguez-Clare (2015), "The Elusive Pro-Competitive Effects of Trade," working paper, Yale University, July 2015.

Atkeson, A., and A. Burstein (2008), "Pricing to Market, Trade Costs, and International Relative Prices," *American Economic Review*, 98(5): 1998–2031.

Behrens, K., and Y. Murata, (2012) "Trade, Competition, and Efficiency," *Journal of International Economics*, 87(1): 1–17.

Bernard, A. B., J. Eaton, J. B. Jensen, and S. Kortum (2003), "Plants and Productivity in International Trade," *American Economic Review,* 93(4): 1268–1290.

Behrens, K., G. Mion, Y. Murata, and J. Südekum, (2014) "Trade, wages, and productivity," *International Economic Review*, 55(4): 1305–1348.

Brandt, L., J. Van Biesebroeck, L. Wang and Y. Zhang (2012), "WTO Accession and Performance of Chinese Manufacturing Firms," working paper, Department of Economics, University of Toronto.

Brandt, L., J. Van Biesebroeck, Y. Zhang (2012), "Creative Accounting or Creative Destruction: Firm Level Productivity Growth in Chinese Manufacturing", *Journal of Development Economics*, 97(2): 339–351.

Cabral, L., and J. Mata (2003), "On the Evolution of the Firm Size Distribution: Facts and Theory," *American Economic Review* 93: 1075–1090.

Caliendo, L. and F. Parro (2015), "Estimates of the Trade and Welfare Effects of NAFTA," *Review of Economic Studies*, 82(1): 1–44.

de Blas, B., and K. Russ (2015), "Understanding Markups in the Open Economy under Bertrand Competition," *American Economic Journal: Macroeconomics*, 7(2): 157–80.

di Giovanni, J., A. A. Levchenko and J. Zhang (2014), "The Global Welfare Impact of China: Trade Integration and Technological Change," *American Economic Journal: Macroeconomics*, 6(3): 153–183.

De Loecker, J. and F. Warzynski (2012), "Markups and Firm-level Export Status," *American Economic Review*, 102(6): 2437–2471.

Devereux, M. B and K. M. Lee (2001), "Dynamic Gains from International Trade with Imperfect Competition and Market Power," *Review of Development Economics*, 5(2): 239–255.

Eaton, J. and S. Kortum (2002), "Technology, Geography, and Trade," *Econometrica*, 70(5): 1741–1779.

Eaton, J., S. Kortum, and S. Sotelo (2013), "International Trade: Linking Micro and Macro," in *Advances in Economics and Econometrics*: 1st ed. Vol 2. Cambridge: Cambridge University Press: 329–370.

Edmond, C., V. Midrigan, and D. Y. Xu (2015), "Competition, Markups, and the Gains from International Trade," *American Economic Review,* 105(10): 3183–3221.

Epifani, P., and G. Gancia (2011), "Trade, markup heterogeneity and misallocations," *Journal of International Economics*, 83(1): 1–13.

Feenstra, R. C. (2014), "Restoring the Product Variety and Pro-competitive Gains from Trade with Heterogeneous Firms and Bounded Productivity," NBER Working Paper No. 19833, January 2014.

Goldberg, P. K., J. De Loecker, A. K. Khandelwal, and N. Pavcnik (2015), "Prices, Markups and Trade Reform," *Econometrica*, forthcoming.

Head, K., T. Mayer, and M. Thoenig (2014), "Welfare and Trade without Pareto," *American Economic Review (Papers and Proceedings)*, 104(5): 310–316.

Helpman, E., M. Melitz, and Y. Rubinstein (2008), "Estimating Trade Flows: Trading Partners and Trading Volumes." *Quarterly Journal of Economics* 123: 441–487.

Holmes, T. J., W.-T. Hsu, and S. Lee (2014), "Allocative Efficiency, Mark-ups, and the Welfare Gains from Trade," *Journal of International Economics*, 94(2): 195–206.

Hsieh, C.-T. and P. J. Klenow (2009), "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124(4): 1403–1448.

Hsieh, C.-T. and R. Ossa (2015), "A Global View of Productivity Growth in China," working paper, Booth School of Business, University of Chicago.

Karabarbounis, L., and B. Neiman (2014), "The Global Decline of the Labor Share," *Quarterly Journal of Economics*, 129(1): 61–103.

Levinsohn, J. A., and A. K. Petrin (2003), "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 70(2): 317–342.

Lu, Y. and L. Yu (2015), "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession," *American Economic Journal: Applied Economics*, 7(4): 221–253.

Melitz, M., and G. Ottaviano (2008), "Market Size, Trade, and Productivity," *Review of Economic Studies,* 75(1): 295–316.

Melitz, M. J., and S. J. Redding (2015), "New Trade Models, New Welfare Implications," *American Economic Review*, 105(3): 1105–46.

Neary, J. P. (2003), "Globalization and Market Structure," *Journal of the European Economic Association*, 1: 245–271.

Olley, G. S., and A. Pakes (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica* 64, 1263–1298

Ottaviano, G., T. Tabuchi, and J.-F. Thisse (2002), "Agglomeration and Trade Revisited," *International Economic Review,* 43(2): 409–435.

Peters, M. (2012) "Heterogenous Mark-Ups, Growth and Endogenous Misallocation," working paper, Yale University.

Restuccia, D., and R. Rogerson (2008), "Policy Distortions and Aggregate Productivity with Heterogeneous Plants," *Review of Economic Dynamics*, 11: 707–720.

Salvo, A. (2010), "Inferring Market Power under the Threat of Entry: The Case of the Brazilian Cement Industry," *RAND Journal of Economics*, 41(2): 326–350.

Schmitz, Jr. J. A. (2005), "What Determines Productivity? Lessons from the Dramatic Recovery of the U.S. and Canadian Iron Ore Industries Following Their Early 1980s Crisis," *Journal of Political Economy*, 113(3): 582–625.

Song, Z., K. Storesletten, and F. Zilibotti (2011), "Growing Like China," *American Economic Review*, 101: 202–241.

Trefler, D. (2004), "The Long and Short of the Canada-U.S. Free Trade Agreement," *American Economic Review*, 94(4): 870–895.

Tybout, J. R. (2003), "Plant- and firm-level evidence on 'New' Trade Theories," in E. Kwan Choi and James Harrigan (Eds.), *Handbook of International Trade*, Blackwell Pub.: 388–415.

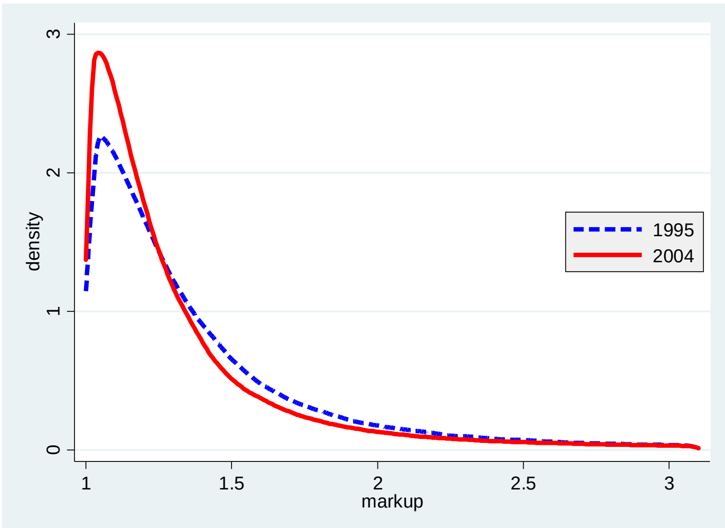

Figure 1: Markup Distributions (1995 versus 2004)

Table 1: Detailed Markup Distributions

	All firms		Exporters		Non-exporters	
Year	1995	2004	1995	2004	1995	2004
Mean	1.428	1.372	1.340	1.318	1.432	1.379
Std. dev.	0.495	0.479	0.431	0.438	0.498	0.483
p1	1.005	1.004	1.003	1.004	1.005	1.004
p5	1.022	1.019	1.017	1.017	1.023	1.019
p10	1.044	1.036	1.034	1.032	1.045	1.037
p25	1.114	1.091	1.084	1.077	1.116	1.093
p50	1.262	1.207	1.120	1.168	1.266	1.213
p75	1.538	1.437	1.414	1.362	1.544	1.447
p90	2.015	1.893	1.784	1.747	2.023	1.909
p95	2.464	2.379	2.199	2.183	2.475	2.400
p99	3.528	3.509	3.299	3.364	3.537	3.523

Table 2: SMM Results

		1995		2004	
Predetermined					
w	Relative wages (the ROW to China)	10.5		5.3	
R1	China's manufacturing sales ($b)	918,291		2,343,328	
R2	ROW's manufacturing sales ($b)	9,397,500		14,737,500	
σ	Inferred from p99 markup	1.40		1.40	
Moments for SMM		**Data**	**Model**	**Data**	**Model**
import share		0.130	0.144	0.222	0.262
export share		0.153	0.190	0.249	0.277
relative number of firms		0.210	0.219	0.596	0.616
fraction of exporters		0.044	0.024	0.105	0.062
mean cost share for exporters		0.845	0.798	0.801	0.804
std of cost share for exporters		0.135	0.142	0.142	0.124
p50 markup for exporters		1.120	1.212	1.168	1.203
p95 markup for exporters		2.199	2.457	2.183	1.839
mean cost share for non-exporters		0.789	0.712	0.829	0.775
std of cost share for non-exporters		0.147	0.187	0.139	0.152
p50 markup for non-exporters		1.266	1.391	1.213	1.264
p95 markup for non-exporters		2.475	2.775	2.400	2.056
Parameter values		**Estimates**	**s.e.**	**Estimates**	**s.e.**
τ, trade cost		2.311	0.020	1.664	0.005
γ, measure of goods		0.261	0.002	0.849	0.005
λ_1, Poisson parameter, China		2.442	0.062	2.607	0.040
λ_2, Poisson parameter, ROW		5.286	0.061	5.828	0.063
μ_1, mean of log productivity, China relative to ROW		-2.401	0.024	-1.785	0.009
η_1, std of log productivity, China		0.444	0.008	0.410	0.001
η_2, std of log productivity, ROW		0.349	0.016	0.293	0.011
Simulated macro moments under estimated parameters		**Data**	**Model**	**Data**	**Model**
w		10.5	10.3	5.3	5.3
R1		918,291	954,812	2,343,328	2,398,028
R2		9,397,500	8,410,637	14,737,500	13,974,893

Notes: All units, if any, are in billions USD, current price. The import share is the import penetration ratio, i.e. IM/(R1-EX+IM), and the export share is the total export divided by the same denominator. All the cost share moments are weighted by firms' revenues. Recall that a firm's cost share is the inverse of its markup. p# denotes the #-th percentile.

Table 3: Jacobian Matrix

moments	τ	γ	λ_1	λ_2	μ_1	η_1	η_2
import share	-0.514	0.005	-0.076	0.002	-0.246	-0.004	0.586
export share	-0.977	0.007	0.087	-0.070	1.169	0.726	-0.345
relative number of firms	0.316	0.775	0.110	-0.013	0.479	0.212	-0.922
fraction of exporters	-0.214	0.001	0.007	-0.012	0.154	0.190	-0.026
mean cost share for exporters	-0.024	0.001	0.013	0.006	0.026	-0.102	-0.062
std of cost share for exporters	0.009	-0.012	-0.009	-0.012	-0.022	-0.139	0.074
p50 markup for exporters	0.038	0.009	-0.020	-0.005	-0.029	0.168	0.034
p95 markup for exporters	0.369	-0.132	-0.185	-0.164	-0.594	-12.864	1.008
mean cost share for non-exporters	-0.109	-0.001	0.019	0.002	-0.066	-0.367	0.092
std of cost share for non-exporters	0.070	-0.001	-0.006	-0.001	0.031	0.186	-0.029
p50 markup for non-exporters	0.176	0.007	-0.037	-0.004	0.141	0.619	-0.189
p95 markup for non-exporters	1.019	-0.031	-0.111	-0.025	0.583	2.772	-0.522

Notes: Each entry of this table gives the rate of change of a moment to a parameter. This is based on the benchmark estimation of the 2004 model. The larger the absolute value of the rate of change, the more sensitive this moment is to the parameter, and the more useful this moment is in identifying this parameter.

Table 4: Counter-factual Analysis

Panel A: Counter-factual from 2004 estimates

	Under 2004 estimates	τ at 1995	% change	Autarky	% change
τ, trade cost	1.664	2.311		1,000,000	
Welfare					
Total Welfare	1.90E+21	1.73E+21	9.4%	1.42E+21	33.4%
W_Prod	1.04E+15	9.78E+14	6.8%	8.44E+14	23.8%
W_A	0.965	0.945	2.1%	0.897	7.5%
W_TOT	1.003	1.000	0.3%	1.000	0.3%
Relative contribution					
Pro-competitive effects			25.4%		23.3%
Importance of W_A			22.3%		22.4%

Panel B: Counter-factual from autarky

	Autarky	10% import share	% change from autarky	20% import share	% change from 10% import share
τ, trade cost	1,000,000	2.252		1.810	
Welfare					
Total Welfare	1.42E+21	1.74E+21	22.6%	1.85E+21	6.0%
W_Prod	8.44E+14	9.81E+14	16.2%	1.02E+15	4.3%
W_A	0.897	0.946	5.5%	0.960	1.5%
W_TOT	1.000	1.000	0.0%	1.002	0.2%
Relative contribution					
Pro-competitive effects			24.2%		27.6%
Importance of W_A			24.2%		24.6%

Notes: In Panel A, all the analysis is done under 2004 estimates, and only the trade cost (τ) changes. The reported percentage changes in this panel are under the changes from the corresponding τ to 2004's τ. Panel B reports results when τ is changed from an inhibitive level (autarky) to the level that entails 10%, and then from 10% to 20%, with other parameters fixed at the 2004 estimates.

Table 5: SMM Results (Symmetric Countries)

		1995		2004	
Predetermined					
w	Relative wages (the ROW to China)	1.0		1.0	
R1	China's manufacturing sales ($b)	918291		2343328	
R2	ROW's manufacturing sales ($b)	918291		2343328	
σ	Inferred from p99 markup	1.40		1.40	
Moments		**Data**	**Model**	**Data**	**Model**
import share		0.130	0.053	0.222	0.117
export share		0.153	0.049	0.249	0.114
relative number of firms		0.210	0.213	0.596	0.611
fraction of exporters		0.044	0.064	0.105	0.140
mean cost share for exporters		0.845	0.731	0.801	0.747
std of cost share for exporters		0.135	0.158	0.142	0.142
p50 markup for exporters		1.120	1.370	1.168	1.334
p95 markup for exporters		2.199	2.564	2.183	2.052
mean cost share for non-exporters		0.789	0.759	0.829	0.793
std of cost share for non-exporters		0.147	0.170	0.139	0.148
p50 markup for non-exporters		1.266	1.289	1.213	1.230
p95 markup for non-exporters		2.475	2.399	2.400	1.995
Parameter values		**Estimate**	**s.e.**	**Estimate**	**s.e.**
τ, trade cost		2.329	0.008	1.738	0.003
γ, measure of goods		0.228	0.002	0.699	0.003
λ, Poisson parameter, China		3.635	0.010	4.219	0.080
η, std. of log productivity		0.399	0.003	0.407	0.005

Notes: All the units, if any, are in billions USD, current price. For the detailed definition of moments, see Table 2.

Table 6: Counter-factual Analysis (Symmetric Countries)

Panel A: Counter-factual from 2004 estimates

	Under 2004 estimates	τ at 1995	% change	Autarky	% change
τ, trade cost	1.738	2.329		1,000,000	
Welfare					
Total Welfare	2.30E+19	2.24E+19	2.7%	2.13E+19	8.1%
W_Prod	1.31E+13	1.28E+13	2.1%	1.24E+13	5.4%
W_A	0.964	0.958	0.6%	0.9406	2.5%
Relative contribution					
Importance of W_A			23.7%		31.4%

Panel B: Counter-factual from autarky

	Autarky	10% import share	% change from autarky	20% import share	% change from 10% import share
τ, trade cost	1,000,000	1.815		1.465	
Welfare					
Total Welfare	2.13E+19	2.29E+19	7.5%	2.37E+19	3.6%
W_Prod	1.24E+13	1.30E+13	5.0%	1.34E+13	3.1%
W_A	0.941	0.964	2.4%	0.9681	0.5%
Relative contribution					
Importance of W_A			32.5%		13.3%

Notes: Under symmetric countries, W_TOT = 1. In Panel A, all the analysis is done under 2004 estimates, and only the trade cost (τ) changes. The reported percentage changes in this panel are under the changes from the corresponding τ to 2004's τ. Panel B reports results when τ is changed from an inhibitive level (autarky) to the level that entails 10%, and then from 10% to 20%, with other parameters fixed at the 2004 estimates.

Table 7: Robustness Check of Counter-factual Analyses

Robustness Check 1: Based on 1995 Estimates

	Under 1995 estimates	τ at 2004	% change to τ at 2004	Autarky	% change from autarky to τ at 1995
τ, trade cost	2.311	1.664		1,000,000	
Welfare					
Total Welfare	1.85E+19	1.99E+19	7.7%	1.43E+19	28.7%
W_Prod	2.78E+13	2.95E+13	6.0%	2.29E+13	21.2%
W_A	0.943	0.957	1.5%	0.889	6.1%
W_TOT	1.002	1.003	0.1%	1.000	0.1%
Relative contribution					
Pro-competitive effects			20.8%		21.6%
Importance of W_A			19.3%		21.1%

Robustness Check 2: Under Raw Markups

	Under 2004 estimates	τ at 1995	% change	Autarky	% change
τ, trade cost	1.654	2.080		1,000,000	
Welfare					
Total Welfare	2.90E+13	2.74E+13	5.8%	2.43E+13	19.2%
W_Prod	1.57E+07	1.50E+07	4.5%	1.37E+07	14.9%
W_A	0.963	0.951	1.2%	0.925	4.0%
W_TOT	0.997	0.997	0.0%	1.000	-0.3%
Relative contribution					
Pro-competitive effects			21.1%		19.6%
Importance of W_A			21.1%		21.1%

Robustness Check 3: Using the 97.5th percentile to Infer Sigma

	Under 2004 estimates	τ at 1995	% change	Autarky	% change
τ, trade cost	1.685	2.161		1,000,000	
Welfare					
Total Welfare	4.49E+15	4.22E+15	6.4%	3.69E+15	21.8%
W_Prod	2.47E+09	2.35E+09	5.1%	2.13E+09	15.7%
W_A	0.963	0.951	1.2%	0.918	4.9%
W_TOT	1.004	1.004	0.0%	1.000	0.4%
Relative contribution					
Pro-competitive effects			19.4%		24.0%
Importance of W_A			19.4%		22.4%

Notes: In the first robustness check, the analysis is based on the 1995 estimate and we change τ to the 2004 level. In the next two robustness checks, analyses are done based on 2004 estimates, as in the benchmark case.

Table 8: The Effect of Tariffs

Panel A: Counter-factual based on 2004 estimates

	Under 2004 estimates	Tariff at 1995, non-tariff τ at 2004	% change	Tariff at 1995, non-tariff τ at 1995	% change	Relative contribution of tariff reduction
τ, trade cost	1.664	1.845		2.311		
Welfare						
Total Welfare	1.90E+21	1.83E+21	3.7%	1.73E+21	9.4%	39.6%
W_Prod	1.04E+15	1.01E+15	2.9%	9.78E+14	6.8%	42.8%
W_A	0.965	0.959	0.6%	0.945	2.1%	29.9%
W_TOT	1.003	1.002	0.1%	1.000	0.3%	44.8%
Relative contribution						
Pro-competitive effects			20.3%		25.4%	
Importance of W_A			16.8%		22.3%	

Panel B: Counter-factual based on 1995 estimates

	Under 1995 estimates	Tariff at 2004, non-tariff τ at 1995	% change	Tariff at 2004, non-tariff τ at 2004	% change	Relative contribution of tariff reduction
τ, trade cost	2.311	2.083		1.664		
Welfare						
Total Welfare	1.85E+19	1.90E+19	2.7%	1.99E+19	7.7%	35.2%
W_Prod	2.78E+13	2.84E+13	2.1%	2.95E+13	6.0%	34.7%
W_A	0.943	0.949	0.7%	0.957	1.5%	44.3%
W_TOT	1.002	1.001	0.0%	1.003	0.1%	
Relative contribution						
Pro-competitive effects			22.8%		20.8%	
Importance of W_A			24.3%		19.3%	

Notes: In Panel A, all the analysis is done under 2004 estimates, and only the trade cost (τ) changes. The reported percentage changes in this panel are under the changes from the corresponding τ to 2004's τ. Panel B reports results under 1995 estimates.

Table 9A: Estimation Result in Multi-Sector Model (Part A)

		Predetermined		γ			τ			Tariff			Non-tariff τ		
cic2d	Industry definition	σ	α	1995	2004	% change	1995	2004	% change	1995	2004	% change	1995	2004	% change
13	Food processing	1.51	0.049	0.018	0.044	139.1	2.47	2.347	-4.9	25.6	16.6	-35.2	1.97	2.01	2.5
14	Food manufacturing	1.33	0.017	0.009	0.018	109.2	4.62	2.49	-46.1	17.5	9.9	-43.6	3.93	2.27	-42.3
15	Beverage manufacturing	1.21	0.014	0.009	0.015	72.4	4.80	3.33	-30.7	25.3	7.7	-69.8	3.83	3.09	-19.3
16	Tobacco processing	1.22	0.014	0.0003	0.0002	-29.8	4.49	4.81	6.9	37.9	9.8	-74.3	3.26	4.38	34.4
17	Textile industry	1.49	0.059	0.013	0.049	269.5	1.88	1.69	-10.4	19.7	7.6	-61.4	1.57	1.57	-0.3
18	Garments & other fiber products	1.37	0.023	0.009	0.028	204.7	3.52	2.91	-17.2	10.8	9.2	-15.0	3.18	2.67	-16.0
19	Leather, furs, down & related products	1.39	0.016	0.006	0.014	136.9	1.96	1.61	-18.0	9.9	5.5	-44.3	1.79	1.53	-14.6
20	Timber processing, bamboo, cane, palm fiber & straw products	1.40	0.011	0.009	0.026	198.8	2.10	1.64	-21.9	7.8	2.6	-67.1	1.95	1.60	-17.9
21	Furniture manufacturing	1.26	0.008	0.005	0.015	215.2	2.47	1.92	-22.2	8.3	1.0	-88.0	2.28	1.90	-16.6
22	Papermaking & paper products	1.48	0.020	0.008	0.025	200.5	2.59	2.16	-16.3	23.7	4.0	-83.0	2.09	2.08	-0.5
23	Printing industry	1.29	0.009	0.010	0.027	157.5	2.68	2.28	-15.1	5.3	0.9	-83.5	2.55	2.26	-11.4
24	Cultural, educational & sports goods	1.35	0.007	0.002	0.009	254.9	2.11	1.72	-18.7	4.1	1.5	-64.3	2.03	1.70	-16.6
25	Petroleum processing & coking	1.45	0.050	0.001	0.006	346.7	1.96	1.54	-21.6	8.6	5.0	-42.2	1.80	1.46	-18.9
26	Raw chemical materials & chemical products	1.50	0.072	0.015	0.073	382.9	2.51	1.74	-30.5	14.6	7.2	-51.0	2.19	1.62	-25.7
27	Medical & pharmaceutical products	1.33	0.017	0.004	0.007	71.9	4.43	2.76	-37.7	6.9	3.8	-44.9	4.15	2.66	-35.8
28	Chemical fiber	2.01	0.010	0.001	0.003	337.5	3.16	2.23	-29.4	22.0	4.9	-77.7	2.59	2.12	-17.9
29	Rubber products	1.50	0.010	0.003	0.009	237.4	2.09	1.84	-11.8	20.2	11.0	-45.6	1.74	1.66	-4.5
30	Plastic products	1.54	0.027	0.011	0.045	320.7	1.76	1.72	-2.4	13.9	5.4	-61.0	1.55	1.63	5.4
31	Nonmetal mineral products	1.35	0.050	0.035	0.094	172.8	4.62	2.39	-48.3	12.8	5.9	-54.0	4.10	2.26	-44.9
32	Smelting & pressing of ferrous metals	1.78	0.092	0.005	0.013	159.1	2.46	2.17	-11.6	10.9	4.9	-55.2	2.22	2.07	-6.6
33	Smelting & pressing of nonferrous metals	1.67	0.031	0.002	0.009	294.3	2.12	1.83	-13.9	7.7	3.9	-49.4	1.97	1.76	-10.7
34	Metal products	1.43	0.032	0.014	0.048	249.6	1.98	1.76	-10.8	13.2	4.0	-69.9	1.75	1.70	-2.8
35	Ordinary machinery	1.50	0.052	0.017	0.084	393.0	3.07	1.64	-46.6	17.5	5.1	-71.0	2.61	1.56	-40.3
36	Special purpose equipment	1.35	0.030	0.011	0.038	241.5	2.41	1.61	-33.2	16.6	5.3	-68.2	2.07	1.53	-26.0
37	Transport equipment	1.36	0.076	0.014	0.036	161.0	2.62	2.18	-16.8	43.5	12.7	-70.8	1.83	1.93	5.9
39	Electric equipment & machinery	1.51	0.061	0.012	0.037	197.9	1.71	1.53	-10.5	11.3	3.0	-73.0	1.54	1.48	-3.4
40	Electronic & telecommunications equipment	1.34	0.121	0.005	0.017	271.3	2.19	1.51	-31.1	13.5	1.3	-90.5	1.93	1.49	-22.8
41	Instruments, meters, cultural & office equipment	1.35	0.013	0.004	0.012	194.4	1.85	1.52	-18.2	15.7	4.3	-72.6	1.60	1.45	-9.2
42	Other manufacturing	1.32	0.009	0.006	0.016	173.0	2.30	1.68	-26.9	8.8	2.8	-67.8	2.12	1.64	-22.7
Mean		1.44	0.034	0.01	0.03	211.52	2.72	2.09	-21.23	15.64	5.74	-61.87	2.35	1.97	-13.77
Standard deviation		0.17	0.029	0.01	0.02	95.89	0.96	0.70	13.23	9.12	3.66	17.25	0.80	0.62	16.52
Max		2.01	0.121	0.03	0.09	392.98	4.80	4.81	6.95	43.46	16.57	-14.99	4.15	4.38	34.39
Min		1.21	0.007	0.00	0.00	-29.81	1.71	1.51	-48.28	4.08	0.87	-90.54	1.54	1.45	-44.90

Table 9B: Estimation Result in Multi-Sector Model (Part B)

cic2d	Industry definition	λ_1 1995	λ_1 2004	λ_1 % change	λ_2 1995	λ_2 2004	λ_2 % change	μ_1 1995	μ_1 2004	μ_1 % change	η_1 1995	η_1 2004	η_1 % change	η_2 1995	η_2 2004	η_2 % change
13	Food processing	2.78	3.05	9.9	5.40	6.9	26.8	-2.37	-1.67	29.8	0.43	0.46	8.2	0.38	0.37	-4.8
14	Food manufacturing	3.03	3.11	2.5	4.25	4.6	8.7	-1.51	-1.50	0.7	0.15	0.34	136.2	0.33	0.34	0.2
15	Beverage manufacturing	3.05	3.24	6.2	5.82	4.5	-23.1	-1.20	-1.23	-2.7	0.11	0.22	95.7	0.09	0.16	82.1
16	Tobacco processing	2.75	3.18	15.8	6.00	5.6	-6.3	-2.38	-1.33	44.0	0.34	0.44	28.6	0.27	0.20	-23.6
17	Textile industry	3.04	3.25	6.9	5.73	6.3	10.2	-2.36	-1.78	24.6	0.35	0.38	9.2	0.35	0.17	-50.8
18	Garments & other fiber products	3.03	3.22	6.2	5.27	6.6	25.5	-2.15	-0.93	56.7	0.55	0.42	-23.9	0.11	0.42	269.7
19	Leather, furs, down & related products	2.85	3.21	12.7	5.13	4.6	-10.4	-2.19	-1.75	20.1	0.33	0.37	11.1	0.44	0.26	-40.3
20	Timber processing, bamboo, cane, palm fiber & straw products	2.85	2.98	4.7	5.26	5.4	2.7	-2.40	-1.74	27.5	0.41	0.32	-20.0	0.40	0.25	-38.7
21	Furniture manufacturing	2.51	2.87	14.4	5.53	5.0	-9.6	-2.03	-1.66	18.1	0.24	0.37	56.4	0.26	0.08	-70.6
22	Papermaking & paper products	3.02	2.76	-8.4	5.59	6.1	9.1	-2.33	-1.79	23.3	0.29	0.41	43.3	0.52	0.44	-16.4
23	Printing industry	2.97	2.61	-12.2	6.41	5.6	-12.7	-2.37	-1.78	24.9	0.35	0.42	18.7	0.09	0.18	106.3
24	Cultural, educational & sports goods	2.44	3.02	23.9	5.06	4.6	-8.6	-2.14	-1.70	20.5	0.38	0.42	9.0	0.28	0.15	-46.4
25	Petroleum processing & coking	2.70	2.87	6.3	5.37	6.1	13.8	-2.25	-1.84	18.3	0.21	0.32	51.8	0.36	0.32	-12.3
26	Raw chemical materials & chemical products	2.63	1.97	-25.1	4.84	6.7	39.0	-2.52	-1.92	23.7	0.43	0.51	17.1	0.52	0.36	-31.1
27	Medical & pharmaceutical products	2.99	2.66	-11.1	6.23	5.0	-19.4	-2.09	-1.61	23.1	0.54	0.50	-8.3	0.17	0.39	130.7
28	Chemical fiber	2.44	2.89	18.2	5.47	4.5	-17.6	-2.59	-1.75	32.5	0.46	0.26	-43.3	0.51	0.44	-14.5
29	Rubber products	3.36	2.61	-22.3	5.57	4.6	-18.2	-2.27	-1.72	24.0	0.30	0.37	22.5	0.15	0.15	5.1
30	Plastic products	2.73	3.13	14.6	5.31	5.8	9.1	-2.39	-1.67	30.2	0.31	0.34	11.0	0.21	0.26	22.6
31	Nonmetal mineral products	3.03	3.03	0.1	4.95	5.6	12.5	-1.59	-1.39	12.7	0.25	0.28	11.0	0.20	0.34	65.3
32	Smelting & pressing of ferrous metals	2.87	3.16	10.1	6.50	4.4	-32.5	-2.40	-1.60	33.3	0.06	0.10	59.4	0.34	0.40	20.0
33	Smelting & pressing of nonferrous metals	2.29	2.54	11.2	5.83	5.8	-0.6	-2.46	-1.77	28.1	0.36	0.40	9.5	0.23	0.33	41.7
34	Metal products	3.03	2.83	-6.7	5.54	5.8	5.2	-2.42	-1.82	24.6	0.37	0.39	5.1	0.24	0.09	-60.4
35	Ordinary machinery	2.24	2.50	11.6	4.64	7.3	56.7	-2.44	-1.79	26.8	0.40	0.42	3.8	0.52	0.31	-39.9
36	Special purpose equipment	2.12	2.49	17.3	5.17	6.9	33.3	-2.63	-1.80	31.4	0.34	0.40	19.4	0.52	0.42	-19.5
37	Transport equipment	2.74	2.53	-7.6	6.12	5.9	-3.9	-2.38	-1.72	27.5	0.38	0.42	8.6	0.29	0.30	6.2
39	Electric equipment & machinery	2.44	2.95	20.9	5.93	5.9	0.0	-2.43	-1.77	27.0	0.31	0.40	28.5	0.16	0.34	114.4
40	Electronic & telecommunications equipment	2.41	2.47	2.5	5.81	5.9	1.8	-2.36	-1.77	25.1	0.51	0.53	3.5	0.52	0.44	-16.0
41	Instruments, meters, cultural & office equipment	2.38	2.18	-8.7	4.95	5.8	16.2	-2.41	-1.75	27.5	0.45	0.46	1.9	0.51	0.44	-13.4
42	Other manufacturing	2.73	3.20	17.4	5.36	5.8	8.7	-2.25	-1.74	22.7	0.52	0.43	-17.6	0.34	0.16	-52.4
Mean		2.74	2.84	4.52	5.48	5.64	4.02	-2.25	-1.67	25.03	0.35	0.38	19.19	0.32	0.29	10.80
Standard deviation		0.30	0.34	12.66	0.52	0.81	19.75	0.32	0.21	10.82	0.12	0.09	35.61	0.14	0.11	72.80
Max		3.36	3.25	23.89	6.50	7.27	56.75	-1.20	-0.93	56.74	0.55	0.53	136.22	0.52	0.44	269.74
Min		2.12	1.97	-25.11	4.25	4.39	-32.53	-2.63	-1.92	-2.72	0.06	0.10	-43.25	0.09	0.08	-70.59

Table 10: Counter-factual Analysis in Multiple-Sector Economy

Panel A: Counter-factual from 2004 estimates

	Under 2004 estimates	Trade costs ({τ_s}) at 1995	% change	Autarky	% change
Welfare					
Total Welfare	1.78E+16	1.66E+16	7.24%	1.38E+16	28.2%
W_Prod	1.82E+09	1.72E+09	5.71%	1.50E+09	21.1%
W_A	0.9585	0.9450	1.43%	0.905	5.9%
W_TOT	0.9992	0.9990	0.02%	1.000	-0.1%
Relative contribution					
Pro-competitive effects			20.0%		20.6%
Importance of W_A			19.7%		20.9%

Panel B: The Effect of Tariff, based on 2004 estimates

	Under 2004 estimates	Tariffs at 1995, non-tariff trade costs at 2004	% change	% change (from trade costs in 1995)	Relative contribution of tariff reductions
Welfare					
Total Welfare	1.78E+16	1.73E+16	2.52%	7.24%	34.8%
W_Prod	1.82E+09	1.78E+09	2.09%	5.71%	36.7%
W_A	0.9585	0.9543	0.44%	1.43%	30.8%
W_TOT	0.9992	0.9994	-0.02%	0.02%	-100.0%
Relative contribution					
Pro-competitive effects			16.7%		
Importance of W_A			17.5%		

Notes: Similar to Table 4, all the analyses in Panel A are done under 2004 estimates, and only the trade costs change. The reported percentage changes in this panel are under the changes from the corresponding {τ_s} to 2004's. Panel B reports results on changing tariffs only and calculates the relative contribution of tariff reductions on welfare.

Table 11: Did China Trade-Liberalize the Right Sectors?

Dependent variable	Changes in trade costs between 1995 and 2004				Changes in import tariffs between 1995 and 2004			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sectoral markup at 1995	-2.109**	-1.774**	-1.980*	-1.856	-0.343**	-0.378**	-0.581*	-0.596*
	(0.799)	(0.833)	(1.063)	(1.117)	(0.154)	(0.164)	(0.296)	(0.303)
SOE share		0.242		-0.967		-0.029		0.042
		(0.157)		(0.728)		(0.032)		(0.171)
Log wage at 1995			-0.072	-0.056			-0.065	-0.064
			(0.209)	(0.218)			(0.066)	(0.068)
Log employment at 1995			-0.153	-0.352			-0.021	-0.011
			(0.125)	(0.218)			(0.029)	(0.056)
Log export at 1995			0.166**	0.181**			-0.045***	-0.047**
			(0.077)	(0.087)			(0.016)	(0.017)
Log import at 1995			-0.035	0.060			0.047**	0.044*
			(0.063)	(0.116)			(0.020)	(0.024)
R^2	0.169	0.186	0.386	0.449	0.108	0.114	0.363	0.366

Notes : The regression is weighted by sectoral trade volume and sectoral imports when the dependent variable is the change in trade cost and import tariff, respectively. Note that the sample size is small (29), and hence one should use caution when interpreting the significance levels.
** Significant at the 10 percent level.*
*** Significant at the 5 percent level*
**** Significant at the 1 percent level.*

Table A1: Production Function Estimates

	Panel A: Output Elasticity With Respect to …						Panel B: Returns to Scale				
	Labor		Capital		Materials		Double		Triple		
Industry	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Obs.
Food processing	0.09	[0.07,0.13]	0.03	[0.01,0.05]	0.86	[0.81,0.90]	0.99	[0.98,1.00]	0.99	[0.98,1.00]	104,518
Food manufacturing	0.14	[0.11,0.18]	0.05	[0.02,0.08]	0.82	[0.76,0.87]	1.02	[1.00,1.04]	1.03	[1.00,1.04]	48,295
Beverage manufacturing	0.19	[0.14,0.25]	0.02	[-0.01,0.05]	0.78	[0.71,0.84]	1.01	[0.97,1.04]	1.01	[0.98,1.04]	41,894
Tobacco processing	0.17	[0.03,0.33]	0.24	[0.10,0.35]	0.73	[0.64,0.82]	1.14	[1.05,1.23]	1.14	[1.04,1.22]	731
Textile industry	0.16	[0.11,0.22]	0.04	[0.03,0.05]	0.84	[0.77,0.89]	1.03	[0.99,1.06]	1.02	[0.99,1.05]	113,001
Garments and other fiber products	0.23	[0.15,0.35]	0.05	[0.04,0.07]	0.75	[0.64,0.84]	1.02	[1.00,1.05]	1.02	[1.00,1.05]	72,381
Leather, furs, down and related products	0.20	[0.12,0.28]	0.01	[0.00,0.02]	0.81	[0.73,0.88]	1.01	[1.00,1.03]	1.01	[1.00,1.03]	34,655
Timber processing, bamboo, cane, palm fiber and straw products	0.15	[0.10,0.21]	0.03	[0.03,0.04]	0.83	[0.76,0.88]	1.01	[0.99,1.02]	1.00	[0.99,1.02]	57,283
Furniture manufacturing	0.38	[0.33,0.44]	-0.02	[-0.03,0.00]	0.99	[0.90,1.07]	1.37	[1.30,1.44]	1.38	[1.32,1.46]	34,126
Papermaking and paper products	0.26	[0.23,0.29]	0.05	[0.04,0.06]	0.85	[0.80,0.89]	1.15	[1.13,1.19]	1.16	[1.13,1.20]	55,606
Printing industry	0.24	[0.21,0.26]	0.11	[0.08,0.15]	0.86	[0.77,0.94]	1.24	[1.17,1.29]	1.25	[1.18,1.30]	57,993
Cultural, educational and sports goods	0.23	[0.15,0.34]	0.06	[0.05,0.08]	0.79	[0.70,0.86]	1.07	[1.04,1.11]	1.06	[1.04,1.10]	20,987
Petroleum processing and coking	0.10	[0.07,0.14]	0.06	[0.05,0.07]	0.83	[0.78,0.87]	0.99	[0.98,1.00]	0.99	[0.98,1.00]	10,430
Raw chemical materials and chemical products	0.22	[0.18,0.25]	0.04	[0.03,0.05]	0.72	[0.67,0.76]	0.97	[0.96,0.97]	0.96	[0.96,0.97]	108,197
Medical and pharmaceutical products	0.25	[0.18,0.32]	0.19	[0.13,0.26]	0.65	[0.55,0.74]	1.08	[1.04,1.12]	1.08	[1.04,1.11]	17,595
Chemical fiber	0.05	[0.01,0.09]	0.16	[0.15,0.18]	0.73	[0.69,0.76]	0.94	[0.92,0.95]	0.94	[0.92,0.95]	4,925
Rubber products	0.23	[0.19,0.27]	0.06	[0.06,0.07]	0.79	[0.73,0.83]	1.08	[1.06,1.09]	1.07	[1.06,1.09]	20,664
Plastic products	0.14	[0.09,0.19]	0.06	[0.05,0.07]	0.83	[0.77,0.88]	1.01	[1.00,1.03]	1.01	[1.00,1.03]	92,509
Nonmetal mineral products	0.15	[0.09,0.22]	0.05	[0.04,0.06]	0.80	[0.72,0.86]	0.98	[0.97,1.01]	0.98	[0.97,1.00]	226,792
Smelting and pressing of ferrous metals	0.10	[0.07,0.14]	0.03	[0.03,0.04]	0.85	[0.80,0.90]	0.98	[0.97,0.99]	0.98	[0.97,0.99]	29,102
Smelting and pressing of nonferrous metals	0.12	[0.08,0.16]	0.03	[0.03,0.04]	0.84	[0.79,0.88]	0.99	[0.99,1.00]	0.99	[0.99,1.00]	20,671
Metal products	0.17	[0.13,0.23]	0.09	[0.08,0.11]	0.71	[0.66,0.76]	0.97	[0.96,1.00]	0.97	[0.95,0.99]	117,081
Ordinary machinery	0.20	[0.16,0.26]	0.08	[0.06,0.09]	0.80	[0.73,0.85]	1.07	[1.06,1.09]	1.07	[1.06,1.08]	148,586
Special purpose equipment	0.24	[0.22,0.28]	0.08	[0.06,0.10]	0.79	[0.73,0.85]	1.13	[1.09,1.16]	1.13	[1.10,1.16]	77,157
Transport equipment	0.16	[0.11,0.22]	0.07	[0.06,0.09]	0.76	[0.69,0.82]	0.99	[0.99,1.00]	0.99	[0.98,1.00]	75,943
Electric equipment and machinery	0.15	[0.11,0.21]	0.06	[0.05,0.07]	0.79	[0.73,0.84]	1.00	[0.99,1.01]	1.00	[0.99,1.01]	63,631
Electronic and telecommunications equipment	0.23	[0.17,0.30]	0.10	[0.09,0.11]	0.73	[0.65,0.80]	1.06	[1.05,1.08]	1.06	[1.05,1.08]	48,716
Instruments, meters, cultural and office equipment	0.20	[0.13,0.29]	0.09	[0.07,0.10]	0.72	[0.63,0.79]	1.00	[0.97,1.04]	1.00	[0.96,1.03]	25,494
Other manufacturing	0.21	[0.14,0.29]	0.06	[0.04,0.07]	0.78	[0.70,0.84]	1.02	[1.00,1.06]	1.02	[1.00,1.05]	39,978

Notes: IQR means inter-quartile range. In Panel B, we calculate the r in k^rY=F(kK,kL,kM), where Y,K,L,M are output, capital, labor, and material, respectively. The calculation is local to the data values and our estimate. The columns under "double" and "triple" are the results when k is chosen to be 2 and 3, respectively.