Input Trade Liberalization and Markup Distribution: Evidence from China*

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Abstract

We utilize an unprecedented liberalization episode in China, namely its WTO accession, to estimate the impact of trade liberalization on firm markup and markup distribution. Using a panel data quantile regression, we show that the impact of tariff reduction on markup can be heterogeneous to different firms, resulting in an unevenly distributed markup change across firms. In particular, reduction in output tariff reduces markup and markup dispersion, while reduction in input tariff increases markup and markup dispersion.

Keywords: Trade Liberalization, Input Tariff, Markup Distribution
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1 Introduction

The pro-competitive effect of trade liberalization emphasizes that increasing international competition can force domestic firms to reduce their markup and also the overall markup dispersion (Levinsohn (1993), Harrison (1994), Lu and Yu (2015)).[1] However, this insight is incomplete when intermediate inputs account for two-thirds of international trade (Johnson and Noguera (2012)). In an imperfectly competitive market, lowering tariffs on imported inputs induces reduction of production costs. Since firms may only partly pass through the cost reduction, their markup rises. Moreover, the impact of input tariff reduction on markup can be heterogeneous to different firms, resulting in an unevenly distributed markup change across firms.

This paper mainly estimates the impact of input trade liberalization on the distribution of firm markup. As its commitment to joining the World Trade Organization (WTO), China substantially reduced its average tariff on manufacturing products within just a few years (Brandt et al. (2017)). The simultaneous reduction in output and input tariffs has heterogeneous impact on the level and dispersion of firm markup. As shown in the left panel of Figure 1, both the average tariff and the standard deviation of tariffs across six-digit HS products dropped substantially in 2001. The right panel of Figure 1 then highlights that around 75% of China's imports are intermediate inputs, while most of the remainder are capital goods.[2]

[Figure 1 about here]

Thus, a large-scale trade reform has profound impacts on firms that go beyond the competitive effect. On the one hand, declines in output tariffs (i.e., tariffs on final goods) induce firms to reduce prices for their products due to import competition. On the other hand, firms that import inputs may benefit from lower marginal costs due to reductions in input tariffs (i.e., tariffs on intermediate inputs). When the price decline is small relative to the decline in input costs, firm's markup increases. This is an insight highlighted by De Loecker et al. (2016), who find incomplete cost pass-through to prices and rising markups for Indian firms responding to input tariff liberalization. Similarly, Brandt et al. (2017), Fan et al. (2018) and Xiang et al. (2017) investigate how input trade liberalization affects Chinese firms' markup level. Departing from the literature, this paper focuses on how output and

[1] Melitz and Ottaviano (2008), De Blas and Russ (2015), Edmond et al. (2015), Feenstra and Weinstein (2017), Arkolakis et al. (2019) use different variable-markup models to present the pro-competitive effect of trade.

[2] A large share of Chinese imports is for export processing (Yu (2015); Manova and Yu (2016)), which is duty free. However, input share of non-processing imports is still around 75-80%, verifying the importance of tariffs on intermediate inputs.

input tariff reductions affect the overall distribution of firm markups. This is important since focusing on the average effect of tariff reductions masks the heterogenous response of firms.

Using detailed firm level data from China, we obtain two novel empirical findings. Firstly, output tariff reduction reduces markup and markup dispersion, while input tariff reduction increases markup and markup dispersion.[3] To illustrate, the left panel of Figure 2 shows that the overall markup distribution across manufacturing firms shifts rightwards from 2000 to 2007. The right panel shows that from 2000 to 2007, the median markup increases from 0.98 to 1.09, the 90-10 percentile ratio increases from 1.57 to 1.95, and the interquartile range increases from 1.27 to 1.37. So both the level and the dispersion of markups increase after liberalization.

[Figure 2 about here]

To estimate the impacts of tariff reductions on the distribution of markups, we adopt a panel data quantile regression (PDQR) with non-additive firm fixed effect as proposed by Powell and Wagner (2014) and Powell (2019). The panel data quantile regression has two advantages over the cross-sectional quantile regression. First, it allows one to control for time-invariant firm characteristics.[4] Second, the coefficient estimates of the quantile regression imply the impact of the explanatory variables on the overall distribution of the dependent variable. The results show that the elasticity of markup with respect to output tariff is positive, while the elasticity of markup with respect to input tariff is negative, for all percentiles. Furthermore, the markup elasticity with respect to output tariff is 0.08, 0.15 and 0.76 for the 10th, 50th, and 90th markup percentile, respectively, indicating that output tariff reduction lowers markup dispersion. The markup elasticity with respect to input tariff is -0.83, -1.60 and -4.07 for the 10th, 50th, and 90th markup percentile, respectively, indicating that input tariff reduction increases markup dispersion.

Secondly, we investigate the channels through which output and input tariff reductions could affect firm markups and markup distribution. Output tariff reduction lowers markup because it intensifies competition from foreign producers. At the industry level, the intensity of foreign competition could be captured by the import penetration ratio (IPR), defined as the ratio of the total import value to the value of total output. Input tariff reduction increases markup because of the access to cheaper foreign inputs. At the industry level, the importance of imported inputs could be captured by the share of firms who use imported inputs. The top panel of Figure 3 examines the heterogeneous effect

[3] We estimate revenue-based markups separately for each sector following De Loecker and Warzynski (2012). More details are provided in Section 2.2.

[4] More details about the panel data quantile regression are discussed in Section 3.2.

of import competition on markup, by separating all industries into two groups based on the sectoral IPR in 2000, where high IPR group includes industries whose IPR is above the median. Both the median and the dispersion (measured as the interquartile range) of markup are growing faster for the low IPR group. The bottom panel groups industries by the fraction of firms who use imported intermediate inputs in 2000. It shows that both the median and the dispersion of markup experience faster growth for the group with larger fraction of importers.

[Figure 3 about here]

Figure 3 implies heterogeneous impact of tariff reduction on markup distribution across industries. To see this, we include in the quantile regression an interaction between the IPR and the output tariff, and an interaction between the fraction of importers and the input tariff. The estimated coefficient for the first interaction is positive, implying larger reduction in markup in response to decreasing output tariffs for all percentiles in industries more exposed to import penetration (i.e., higher IPR). The estimated coefficient for the second interaction is negative. Therefore industries that are more reliant on imported inputs tend to have larger increase in markup for all percentiles due to input tariff reduction.

A few robustness checks are conducted. First, to account for firm turnover during the sample period, we run the quantile regression on a balanced panel of continuing firms as well as on a sample of new entrants. We find pro-competitive effect of output tariff reduction for continuing firms, but not for new entrants. However, for both continuing firms and entrants, input tariff reduction increases markup. Second, ownership matters. State owned firms (SOEs) benefit less from input tariff reduction and are less affected by output tariff reduction, while foreign invested firms benefit more from input tariff reduction. Finally, processing and non-processing firms may respond differently. When we focus on non-processing firms, we find qualitatively similar results on the impact of input tariff reduction, while the impact of output tariff reduction becomes weaker.

Our paper contributes to a growing body of research that highlights the importance of input tariff liberalization.[5] These studies show that input tariff reduction often plays a more important role in influencing firm performance such as productivity, export growth, organizational efficiency, and creation of new products (Amiti and Konings (2007), Goldberg et al. (2010), Topalova and Khandelwal (2011), Yu (2015), Bas (2012), and Chakraborty and Raveh (2018)). De Loecker et al.

[5] See De Loecker and Goldberg (2014) for the most up-to-date review on how trade liberalization affects firm performance.

(2016) provide the first study that accounts for the offseting impacts of input and output tariffs on precisely measured firm markup. They show that the pro-competitive effect of output tariff reduction is largely offset by access to cheaper imported inputs, resulting in rising markups for Indian firms after trade liberalization. Our paper is the first to quantify the impact of input tariff reduction on firm markup distribution.

Our paper also contributes to understanding the impact of China's WTO accession. Yu (2015) shows that input tariff reduction strongly improves non-processing exporters' productivity, while processing imports tend to attenuate this productivity gain. In the same vein, Fan et al. (2015) find that input tariff reduction increases exporters' product quality. Input trade liberalization may also enhance the ability of domestic production to replace imported components, resulting in increasing domestic content in Chinese exports (Kee and Tang (2016)). In comparison, we examine how reductions in output and input tariff affect the distribution of firm markup, which sheds some lights on the impact of trade liberalization on misallocation. In particular, under oligopolistic competition (Atkeson and Burstein (2007)), markup dispersion implies that prices are not aligned with marginal costs, and therefore indicating misallocation in resources. In this case, reduction in output tariff intensifies competition, leading to reduction in markup dispersion and as a results reducing misallocation (Edmond et al. (2015); Hsu et al. (2020); Lu and Yu (2015)). The impact of input tariff reduction on misallocation is less studied. In this case, lowering costs in imported inputs may increase markup dispersion and exacerbate misallocation. In this vein, our study enriches the discussion on welfare gains of trade liberalization based on variable-markup models (Arkolakis et al. (2019)). Finally, in terms of policy implication, our paper suggests that certain types of firms may gain more than other types by lobbying for lower input tariffs but higher output tariffs, which lends support to the insights from the political economy literature (Gawande et al. (2012)).[6]

2 Background and Data Preparation

2.1 China's WTO Accession and Tariff Reduction

China has gradually embraced globalization since the early 1980s. However, the progress was greatly accelerated by its accession to the WTO in December, 2001 (Branstetter and Lardy (2008)). As shown in Figure 1, after its WTO accession, China achieved an annual average growth at as high

[6] We thank a referee for this point.

as 25%, in both export and import values until 2008. Accompanying the accelerated trade growth was a large-scale reduction in tariffs. By 2005, China had fulfilled most of its commitment to cutting tariffs and eliminating non-tariff measures. The import-weighted average tariff across all 6-digit HS goods was reduced from 15% in 1997 to lower than 5% in 2007. Most of the tariff reductions occurred during 2001 and 2002. Equally remarkable was the decline in the standard deviation of tariffs across products over the same period, as shown by the blue dashed line in the figure (right axis). As a result, the post-reform import tariff rates are uniformly low, implying that products with higher initial tariffs underwent larger tariff reductions after trade liberalization. It indicates that there was little policy discretion across sectors in the extent of trade liberalization (Brandt et al. (2017)). This would partly alleviate the endogeneity concern related to the tariff reduction. Furthermore, in the quantile regression, we control for non-additive firm time-invariant characteristics for the purpose of identification.

To capture the distinct effect of input tariffs on intermediate goods in contrast with output tariffs on final goods, we adopt the extended Chinese Input-Output Table for the benchmark year 2002.[7] The coefficients for the IO matrix (a_{kj}) reflect the cost share of input k for producing output j; that is, $a_{kj} = \frac{input_{kj}}{\sum_k input_{kj}}$. First, we map each of the six-digit HS product codes to a five-digit IO sector category. Tariff data at the six-digit HS level is from the trade analysis and information system (TRAINS). The output tariff for a sector k is then simply the import-weighted average across all 6-digit HS codes within sector k. Finally, the input tariff for each IO sector j is computed as the weighted average of the output tariff, where the weights are given by the IO coefficients:

$$\tau_{jt}^{input} = \sum_k a_{kj} \tau_{kt}^{output} \tag{1}$$

2.2 Estimating Firm Markup

Our main variable of interest is firm markup, defined as the ratio of price to marginal cost. The main production data we use is the Annual Surveys of Industrial Production (ASIP) data, provided by the National Bureau of Statistics of China (NBSC) for the 2000-2007 period. This dataset contains all state-owned enterprises (SOEs) and non-SOEs with annual sales of at least 5 million RMB (around US $ 620,000). It contains detailed firm level production and balance-sheet information such as gross

[7] There are 122 industries in the 2002 China Input-Output Table, including 71 manufacturing industries for which we have constructed output tariffs and input tariffs. Our use of the 2002 IO table is based on the assumption that the input-output structure did not change much over the sample period, which is reasonable for a medium time span and is thus also adopted in the literature (Amiti and Konings (2007); Topalova and Khandelwal (2011)).

output, value-added, employment, capital stock, etc. The dataset forms the basis for major statistics published in China Statistical Yearbooks and has been widely used in economic research. Brandt et al. (2012) provide a detailed description of the data.

Given the limited information on output prices, we adopt the methodology proposed by De Loecker and Warzynski (2012) to estimate firm-level markup. Their approach follows the insight of Hall et al. (1986) and relies on the standard cost minimization conditions, with at least one variable input free of adjustment frictions. One advantage of this method is that it does not depend on the settings of the demand system and can thus be conveniently applied to production data. Under any form of imperfect competition, the relevant markup is pinned down by the variable input's revenue share and its output elasticity.

We briefly describe the insight of De Loecker and Warzynski (2012) below. First, assume a continuous and twice-differentiable production function for firm i,

$$Y_{it} = f\left(K_{it}, L_{it}, M_{it}, \omega_{it}\right) e^{\varepsilon_{it}} \tag{2}$$

where K_{it}, L_{it}, and M_{it} denote capital, labor, and material inputs respectively. ω_{it} stands for firm i's productivity and ε_{it} stands for unexpected i.i.d. productivity shocks. Let $Q_{it} = f\left(K_{it}, L_{it}, M_{it}, \omega_{it}\right)$.

As firms are cost-minimizers, their optimization problem could be captured by the following Lagrangian function:

$$\mathscr{L}\left(K_{it}, L_{it}, M_{it}, \lambda_{it}\right) = P_{m,it}M_{it} + r_{it}K_{it} + w_{it}L_{it} + \lambda_{it}\left(Q_{it} - f\left(K_{it}, L_{it}, M_{it}, \omega_{it}\right)\right) \tag{3}$$

where w_{it}, r_{it}, and $P_{m,it}$ denote the wage rate, rental rate for capital, and price for intermediate inputs, respectively. As long as intermediate inputs remain free of adjustment costs, we can solve the first order condition as,

$$\frac{\partial \mathscr{L}_{it}}{\partial M_{it}} = P_{m,it} - \lambda_{it}\frac{\partial f\left(K_{it}, L_{it}, M_{it}, \omega_{it}\right)}{\partial M_{it}} = 0 \tag{4}$$

where λ_{it} is exactly the marginal cost of production at a certain level of output, because $\frac{\partial \mathscr{L}_{it}}{\partial Q_{it}} = \lambda_{it}$. Then, defining markup as the ratio of price to marginal cost, $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, we can re-arrange equation

(4) and get,

$$\begin{aligned}\mu_{it} &= \frac{P_{it}}{\lambda_{it}} = \frac{P_{it}}{P_{m,it}} \frac{\partial f\left(K_{it}, L_{it}, M_{it}, \omega_{it}\right)}{\partial M_{it}} \\ &= \frac{\frac{M_{it}}{Q_{it}} \frac{\partial f(K_{it}, L_{it}, M_{it}, \omega_{it})}{\partial M_{it}}}{\frac{M_{it} P_{m,it}}{Q_{it} P_{it}}} = \frac{\theta_{m,it}}{\alpha_{m,it}}\end{aligned} \tag{5}$$

where $\theta_{m,it}$ is the output elasticity of intermediate inputs and $\alpha_{m,it}$ is the revenue share of the expenditure on intermediate inputs.

Both the revenue share of input $\alpha_{m,it}$ and the output elasticity $\theta_{m,it}$ need to be estimated with the production function.[8] We estimate the production function for each sector separately. After matching the ASIP data with the IO sector code, we end up with 71 manufacturing sectors. To obtain reliable estimates of output elasticity, we retain firms that have existed for no less than three years. After obtaining the parameter estimates, we apply them to the full sample to obtain firm markups for the full sample.[9]

De Loecker and Warzynski (2012) suggest a two-step estimation procedure, following the control function approach proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). In the first step, we lay out the production function,

$$y_{it} = \theta_l l_{it} + \theta_k k_{it} + \theta_m m_{it} + \rho_{pt} + \omega_{it} + \varepsilon_{it} \tag{6}$$

where θ_l, θ_k, and θ_m are the output elasticities of labor (l), capital (k), and inputs (m) respectively. ω_{it} is the total factor productivity (TFP). All variables are expressed in logarithm form, and the variables y_{it}, and m_{it} are deflated with industry-level output and input deflators from Brandt et al. (2012). To account for regional differences in factor markets within China (Cheng and Morrow (2018)), we also add province-year fixed effects ρ_{pt}.

Material input choice is affected monotonically by the productivity ω_{it} that are observed by firms but not by econometricians, and we can represent material input as,

$$m_{it} = m_{it}\left(\omega_{it}, l_{it}, k_{it}, FX_{it}, FM_{it}\right) \tag{7}$$

[8] The revenue share is $\alpha_{m,it} = \frac{M_{it} P_{m,it}}{P_{it} \frac{Y_{it}}{exp(\hat{\varepsilon}_{it})}}$ instead of $\frac{M_{it} P_{m,it}}{Y_{it} P_{it}}$, which eliminates expenditure variations coming from output variations ε_{it} as we will define in equation (6).

[9] We follow Berkowitz et al. (2017) in retaining firms that have existed for no less than three years for estimation following. Our results are qualitatively robust if we use the sample for estimating markup, instead of the full sample, in the quantile regression. These results are shown in Table 5.

Equation (7) indicates that a firm's input choice is determined by its productivity and factor inputs. It is also affected by the firm's export and import status. We include export status FX_{it} to acknowledge that exporters are faced with different levels of final good demand and may have different input choices. And, we include the importer dummy FM_{it} to account for the fact that importers have different levels of demand for intermediate inputs than do non-importers.

Because more productive firms use more intermediate inputs, we can invert equation (7) and express productivity as a function of inputs, and export and import indicators,

$$\omega_{it} = h\left(m_{it}, l_{it}, k_{it}, FX_{it}, FM_{it}\right) \tag{8}$$

Then, combining equations (6) and (8), we can estimate the following equation non-parametrically:

$$y_{it} = \phi_{it}\left(m_{it}, l_{it}, k_{it}, FX_{it}, FM_{it}\right) + \rho_{pt} + \varepsilon_{it} \tag{9}$$

Estimating equation (9) yields predicted output $\hat{\phi}_{it}$ and error term $\hat{\varepsilon}_{it}$. Then, we can recover productivity as,

$$\omega_{it}\left(\Theta\right) = \hat{\phi}_{it} - \theta_l l_{it} - \theta_k k_{it} - \theta_m m_{it} \tag{10}$$

where $\Theta = (\theta_l, \theta_k, \theta_m)$ is the set of output elasticities. In the second step, we estimate Θ using a GMM approach. We assume that that productivity follows a first order Markov process,

$$\omega_{it} = g\left(\omega_{it-1}\right) + \gamma_x FX_{it-1} + \gamma_m FM_{it-1} + \xi_{it} \tag{11}$$

where ξ_{it} is an i.i.d productivity shock. $g_t\left(.\right)$ is a third order polynomial of ω_{it-1} .We include lagged export and import status to allow for channels of productivity improvement through exporting or importing. A non-parametric regression of equation (11) obtains the innovation to productivity $\xi_{it}\left(\Theta\right)$. As $\xi_{it}\left(\Theta\right)$ is not correlated with the lagged flexible inputs (labor and material) and current capital stock because it is pre-determined, we can then use the moment conditions:

$$E\left[\xi_{it}\left(\Theta\right)\begin{pmatrix} l_{it-1} \\ m_{it-1} \\ k_{it} \end{pmatrix}\right] = 0 \tag{12}$$

to identify Θ. With Θ estimated, we can readily compute the firm-level markup as

$$\hat{\mu}_{it} = \frac{\hat{\theta}_m}{\hat{\alpha}_{m,it}} \tag{13}$$

where $\hat{\alpha}_{m,it} = \frac{M_{it}P_{m,it}}{Y_{it}P_{it}/exp(\hat{\varepsilon}_{it})}$.

For brevity, we present the complete set of estimation parameters in the appendix, including basic statistics on output elasticity, markup level, and the dispersion.

2.3 Descriptive Statistics

As described above, our main firm-level variables are drawn from the Annual Surveys of Industrial Production (ASIP), 2000-2007. We follow Cai and Liu (2009) and Yu (2015) and use the General Accepted Accounting Principles as guidance to clean the data. We then follow Li et al. (2015) and match this dataset with the firm-level trade data from the Customs Administration to obtain information on firms' import status. We drop the top and bottom 1% extreme values for markups, and misreported observations. The data cleaning results in an unbalanced panel of 1,575,162 observations, distributed across 71 industries (126,718 firms in 2000 and 280,296 firms in 2007).

Table 1 presents the summary statistics of key variables used in our empirical investigation. Our major interest is firm level markup, which, after we delete the bottom and top 1% sample, ranges from 0.76 to 2.34. The left panel in Figure 2 shows that after trade liberalization the overall markup distribution across manufacturing firms shifts rightwards from 2000 to 2007. It is worth noting that a substantial fraction of firms exhibit markups smaller than one, because the output elasticity is underestimated when a revenue-based production function is used without firm-level output and input prices (De Loecker and Goldberg (2014)).[10] However, as long as the output and input price biases do not vary over time, the markup level bias will not affect our results because we focus on within firm changes.

Panel A of Table 1 also summarizes firm level control variables we used in later empirical estimations, such as firm import / export status, firm age, productivity, and ownership. Panel B presents the summary statistics for input and output tariffs at the industry level.

Panel C presents two industry level variables, import penetration ratio and importer fraction in 2000. There are substantial variations in the two variables across industries. Finally, Panel D

[10] When a revenue-based production function is estimated, both firm-level output price and input price appear in the residual, and are negatively correlated with the value of inputs.

summarizes firm outputs and inputs, which are used for markup estimation.

[Table 1 about here]

3 Benchmark Results

3.1 Hypothesis Development

We first develop our main testable hypotheses. Since China's WTO accession brought down both the input and output tariffs, our empirical specification needs to account for both to avoid omitted variable bias. The literature has emphasized the pro-competitive effect of output tariff reduction (De Loecker and Goldberg (2014), Fan et al. (2015), Brandt et al. (2017)), and we would expect a negative effect of output tariff on firm markup. On the other hand, the pro-competitive effect also means the markup dispersion will be reduced due to reduction in output tariff (Edmond et al. (2015), Lu and Yu (2015)).

Reduction in input tariffs lowers production costs of domestic firms. On the one hand, this improves firms' performance, including productivity (Amiti and Konings (2007), Topalova and Khandelwal (2011), Kasahara and Rodrigue (2008), Yu (2015), Bas et al. (2016)), learning of foreign technology (Bas and Berthou (2016)), product quality (Halpern et al. (2015), Fan et al. (2015), Bas and Strausskahn (2015)), export growth (Bas (2012), Bas and Strausskahn (2014), Feng et al. (2016)), expansion in input varieties (Goldberg et al. (2010)), and organizational efficiency (Chakraborty and Raveh (2018)), etc. On the other hand, if firms partly pass through the cost reduction to product price, then input tariff reduction would lead to higher markup, as confirmed by De Loecker et al. (2016), Brandt et al. (2017), Fan et al. (2018), and Xiang et al. (2017). So we expect that reduction in input tariffs leads to higher firm markup.

What has not been studied in the literature is how input tariff reduction affects the distribution of markups. A few studies offer useful insights. Notably, Amiti et al. (2014) show that the exchange rate pass-through to consumers depends on firms' productivity and market share. A firm with higher productivity, or a larger market share has lower rate of pass-through. Since both productivity and market share are positively correlated with markup (Melitz and Ottaviano (2008), Atkeson and Burstein (2007)), firms with higher markup have larger market power, and likely have lower pass-through rate of cost reduction. Therefore, input tariff reduction further enlarges the dispersion of firm markup.

This hypothesis receives some support from Chevassuslozza et al. (2013), who find that input trade liberalization enlarges the dispersion in sales across firms with heterogenous productivity.

To summarize, we would expect that in a trade liberalization episode, reduction in output tariffs reduces firm markup as well the dispersion of markup, while reduction in input tariffs increases markup and also the dispersion of markup. In the following sections, we adopt a panel data quantile regression approach to test these hypotheses.

3.2 Panel Data Quantile Regression

A quantile regression minimizes the sum of absolute residuals between the model- and the data- based conditional percentiles (Koenker and Hallock (2001)). The panel data quantile regression (PDQR) includes non-additive fixed effects, and estimates the impact of treatment variables on the outcome distribution (Powell and Wagner (2014), Powell (2019)), which is specified as:

$$\mu_{it} = D_{it}^{'} \times \beta(U_{it}^{*}), \qquad and \qquad U_{it}^{*} \sim U(0,1), \tag{14}$$

where i and t stand for firm and year, respectively. μ_{it} is log markup. D_{it} is the set of all dependent variables, including tariffs and other control variables. $\beta(U_{it}^{*})$ indicates that the parameters are based on a non-separable disturbance term U_{it}^{*}, which follows a uniform distribution. Accordingly, the population regression function is:

$$S_{\mu}(x|D_{it}) = D_{it}^{'} \times \beta(x) \tag{15}$$

$$D_{it} = \begin{pmatrix} \tau_{jt}^{o} \\ \tau_{jt}^{m} \\ Z_{it} \\ \gamma_{t} \end{pmatrix} \tag{16}$$

where $S_{\mu}(x|D_{it})$ is the conditional expectation of μ_{it} at percentile x. The set of all independent variables D_{it} includes output tariff τ_{jt}^{o}, input tariff τ_{jt}^{m}, firm level control variables Z_{it} and year dummy γ_{t}, where j stands for industry. Z_{it} captures time-varying firm level characteristics that could affect markup, such as firm age, TFP, import and export dummy and firm ownership. $\beta(x)$ captures the impacts of input and output tariffs on different markup percentiles $x \in (0,1)$.

Equation (15) is estimated using the generalized methods of moments (GMM). We use firm fixed

effects α_i to control for unobserved firm-specific time-invariant characteristics, that is:

$$U_{it}^* = f(\alpha_i, U_{it}), \qquad and \qquad U_{it}^* \sim U(0,1), \tag{17}$$

where $f(\alpha_i, U_{it})$ is a flexible function and is estimated non-parametrically in the model. The panel data quantile regression allows us to control for unobserved firm characteristics for the purposes of identification. The coefficient β captures the impacts of independent variables D_{it} on the overall markup distribution.

3.3 Baseline Estimation Results

Table 2 presents the baseline results. First, output tariff has positive effects on firm markup for all percentiles, with larger elasticity for higher markup percentiles. In particular, firm markup at the 10th, 50th, and 90th percentiles are reduced by 0.08%, 0.15% and 0.76%, respectively, in response to one percentage point drop in output tariff. Thus reduction in output tariff not only reduces markup level, but also reduces markup dispersion. The impact of input tariff on firm markup is significantly negative for all percentiles, with larger elasticity (in absolute value) for higher markup percentiles. In particular, firm markup at the 10th, 50th, and 90th percentiles increase by 0.83%, 1.60% and 4.07%, respectively, in response to one percentage point drop in input tariff. Thus reduction in input tariff increases markup and markup dispersion. For other control variables, we find that exporters, older firms, and private firms (compared with SOEs and FIEs) have lower markups. In addition, more productive firms tend to charge lower markup at low percentiles, but increase markup at high percentiles.

[Table 2 about here]

Figure 4 plots the estimated elasticity of markup with respect to output and input tariffs from the 10th to the 90th percentiles. The top panel shows that the markup elasticity with respect to output tariff is positive for all percentiles, and is increasing with percentiles. The bottom panel shows that markup elasticity with respect to input tariff is negative for all percentiles, and is decreasing with percentiles. [11]

[11] The panel data quantile regression does not allow for estimating clustered standard errors. As a robustness check, we use the cross-sectional quantile regression with no firm fixed effect, but clustered the standard error at industry-year. The results are shown in Appendix Table A3, and are qualitatively consistent with Table 2. The regression coefficients are plotted in Figure A1.

[Figure 4 about here]

Using the coefficients estimated above, Figure 5 plots the counterfactual cumulative distribution of markups, together with the actual markup distribution in 2000 and 2007. To reduce computation burden, we first use the coefficient estimates from the 10th to the 90th percentiles to interpolate the elasticities from the 1th to the 99th percentiles. Then we multiple the markup elasticity with the actual reduction in tariffs to get the counterfactual changes in markup. Figure 5 shows that the markup distribution moves leftwards and becomes less dispersed with reduction in output tariff, and it moves rightwards and becomes more dispersed with just reduction in input tariff.

[Figure 5 about here]

Table 3 summarizes the total impact of reduction in output and input tariffs on firm markup distribution. To be concrete, from 2000 to 2007 the median value of log markup increases from -0.0251 to 0.0827, the mean markup in log increases from 0.0078 to 0.1412, and the variance increases from 0.0293 to 0.0553. Using the estimated coefficients, we can calculate the counterfactual changes in log markup due to tariff changes, which can then tell us the contribution of input and output tariff changes in explaining the changes in log markup distribution. Our results show that the input tariff reduction contributes about 65.0%, 60.4% and 81.2% of the total change in the median, mean, and variance of log markup, respectively. And the output tariff reduction contributes about -10.6%, -12.6% and -23.5% of the change in the median, mean, and variance of log markup, respectively.

[Table 3 about here]

It is possible that firms adjust their product portfolio in response to trade liberalization. Given heterogeneous markups across products within a firm, competition may force firms to lower markup for high percentile products and drop products with low markup. Therefore we would expect more concentrated within-firm markup distribution when output tariff is reduced. This means that we may underestimate the impact of output tariff reduction on markup. On the other hand, lower costs of imported inputs may induce firms to add more varieties into production and increase markup for high percentile products. It may also encourage firms to switch to products that use more imported inputs. Thus, input tariff reduction is likely to increase markup dispersion within a firm, but the impact on the overall markup distribution would be ambiguous.[12]

[12] Unfortunately, the ASIP data does not report detailed information about product quantity and price within a firm,

4 Mechanism and Robustness

4.1 Mechanism Analysis

In this section, we discuss possible channels through which output and input tariff reduction can affect markup distribution. As we have discussed, reduction in output tariff induces foreign competition, which is more so in sectors with higher import penetration. Reduction in input tariff, on the other hand, brings down input costs, which is more so in sectors where more firms use imported intermediate inputs. To test these mechanisms, we add four extra terms to the benchmark quantile regression model specified in (15): the import penetration ratio (IPR_j) and its interaction with output tariff, the share of importers (IS_j) and its interaction with input tariff.

$$\mu_{it} = D_{it}^{'} \times \beta(U_{it}^{*}) \tag{18}$$

$$D_{it} = \begin{pmatrix} \tau_{jt}^{o} \\ \tau_{jt}^{m} \\ \tau_{jt}^{o} \times IPR_j \\ \tau_{jt}^{m} \times IS_j \\ IPR_j \\ IS_j \\ Z_{it} \\ \gamma_t \end{pmatrix} \tag{19}$$

$$U_{it}^{*} = f(\alpha_i, U_{it}), \qquad and \qquad U_{it}^{*} \sim U(0,1). \tag{20}$$

Accordingly, the elasticity of expected markup at percentile x with repect to input and output tariffs are,

$$\frac{\partial S_{\mu}(x|D_{it})}{\partial \tau_{jt}^{o}} = \beta_1(x) + \beta_3(x) \times IPR_{jt} \tag{21}$$

$$\frac{\partial S_{\mu}(x|D_{it})}{\partial \tau_{jt}^{m}} = \beta_2(x) + \beta_4(x) \times IS_{jt} \tag{22}$$

Table 4 presents the results. To save space, we only include the 25th, 50th and 75th percentiles. In

so we cannot estimate within-firm product level markups. For a subset of firms, we have information on the number of varieties produced by each firm. So we follow Goldberg et al. (2010) and run a regression to see how firms adjust their number of varieties in response to the reduction in output tariff and input tariff. See the online appendix II for a discussion on firms' portfolio adjustment and the regression results.

the first three columns, we add IPR_{jt} and its interaction term with output tariff to the baseline model. The coefficient (β_3) is positive and significant, suggesting that the effect of output tariff reduction on markup is increasing with IPR_{jt}. For example, the median markup elasticity with respect to output tariff is nearly zero in the industry with the first quartile value of IPR. It increases to 0.058 in the industry with the third quartile IPR. In the next three columns, we further include the share of importers (IS_{jt}) and its interaction with input tariff. The coefficient (β_4) is negative and significant, implying that the impact of input tariff is negative and increasingly so when IS is higher. For example, the median markup elasticity with respect to input tariff is -0.74 in the industry with the first quartile of importer share, but is -1.56 in the industry with the third quartile.

[Table 4 about here]

4.2 Robustness Checks

4.2.1 Continuing Firms and Entrants

The number of manufacturing firms more than doubled during 2000 to 2007. For example, there are 126,718 firms in 2000 in our ASIP dataset, in 2007 this number increases to 280,296. This implies large firm turnover. A natural question follows: whether tariff reduction has different effects on the markup of continuing firms versus new entrants. To investigate this possibility, in Table 5, we implement the quantile regression separately using the sample of continuing firms, which is balanced, as well as the sample of new entrants. The first three columns of Table 5 report the estimation results using the continuing firms sample, and the results are qualitatively similar with the baseline results of Table 2. Columns (4)-(6) focus on the sample of new entrants, which are defined following Brandt et al. (2012). The results show that reduction in input tariff increases the 10th and the 50th percentile of markup, but has no statistically significant effect on the markup of firms at the 90th percentile. Reduction in output tariff has no significant impact on the distribution of new entrants' markups. These results in Table 5 imply that the pro-competitive effects induced by output tariff reduction is mainly on continuing firms. Brandt et al. (2017) also find that the pro-competitive effects are most important among incumbents. The effect of input tariff reduction, on the other hand, is found to be significant for both continuing firms and new entrants. Columns (7) to (9) conduct robustness checks by including only the sample used for markup estimation (i.e., firms who have existed for at least three years). The results are qualitatively similar.

[Table 5 about here]

4.2.2 FDI Policy

The deregulation on foreign direct investment (FDI) is another major policy change that happened in the same period from 2000 to 2007. FDI liberalization removes restrictions on foreign invested enterprises, which may improve firm performance because of deregulation or spillover. Since many firms that use imported inputs are multinational firms that also benefit from the FDI liberalization, our estimation may be contaminated due to omitted variable bias. To deal with this identification issue, we follow Lu et al. (2017) to construct a FDI policy variable $FDISector_{jt}$ for each industry j in each year t:

$$FDISector_{jt} = \frac{\sum_{i \in \Omega_j} FDIFirm_{ijt} \times Output_{ijt}}{\sum_{i \in \Omega_j} Output_{ijt}}, \tag{23}$$

where $i \in \Omega_j$ means firm i is in industry j, $FDIFirm_{ijt}$ measures the foreign equity share of firm i in industry j in time t, and $Output_{ijt}$ measures the output of firm i. Thus $FDISector_{jt}$ measures the importance of foreign firms in industry j. The first three columns of Table 6 present the regression results: conditional on FDI share, the coefficient estimates for both output and input tariffs become smaller, and more so for higher markup percentiles. The FDI share itself has a positive coefficient, implying that firms in industries with more presence of FDI tend to have higher markups.

[Table 6 about here]

4.2.3 Heterogeneity in Ownership

In Table 2, we have shown that firms with different ownership differ in their markup and markup distribution. Columns (4)-(6) of Table 6 examine how ownership structure affects the impact of output and input tariffs, by interacting input and output tariffs with indicators for firm ownership. Compared with domestic private firms, foreign invested firms benefit more from input tariff reduction, which is consistent with the fact that they use more imported inputs, and they are also less affected by output tariff reduction. State owned firms benefit less from input tariff reduction, and they are also less responsive to output tariff reduction. It is possible that the state owned firms have larger market power so their markup reduction due to foreign competition is smaller, yet they are also less efficient in using imported inputs so their markup increase due to input tariff reduction is also smaller.

4.2.4 Processing Firms

Recent studies on China's foreign trade have emphasized the role of export processing, which refers to the trade regime in which Chinese producers import inputs (often from their foreign buyers), process and assemble, and finally export the final goods. It has been documented that processing exporters differ from ordinary exporters in choosing inputs, technology, and export destinations, they also differ substantially in productivity. To avoid the noise caused by the processing arrangement, Table 7 presents results using the sample of non-processing firms.[13] It shows that the estimated coefficient of input tariff decreases with percentiles, and the estimated coefficient of output tariff increases with percentiles. Thus our key findings still hold for non-processing firms. Moreover, for non-processing firms, the effect of output tariff reduction on markup is weaker compared with the baseline results. That is consistent with Yu (2015), who finds that the impact of output tariff reduction on productivity is weaker for non-processing firms.

[Table 7 about here]

5 Conclusion

In this paper, we investigate the impact of trade liberalization on the distribution of firm markup. Our empirical study applies a quantile panel regression approach to a large-scale firm-level data from China. The novel part of our paper is our focus on the impact of input tariff reduction on firm markup and markup dispersion, while a large body of research focuses on the pro-competitive effect of output tariff reduction. In an imperfectly competitive market, firms may not pass through completely their input cost reduction due to lower input tariff. So input tariff liberalization may induce higher firm markup. Crucially, we find that the elasticity of markup with respect to input tariff, is increasing with markup percentiles. Thus input trade liberalization leads to larger markup dispersion. We explore possible mechanisms through which the reduction in output and input tariffs may work to affect markups. We show that the effect of output tariff is stronger in sectors with higher import penetration, while the effect of input tariff is stronger in sectors where more firms use imported intermediate inputs.

[13] Although we do not have exact information on whether a manufacturing firm is a processing exporter. We do know processing exporters export a very high share of their total output. So here we define processing exporters as these firms who export all of their products.

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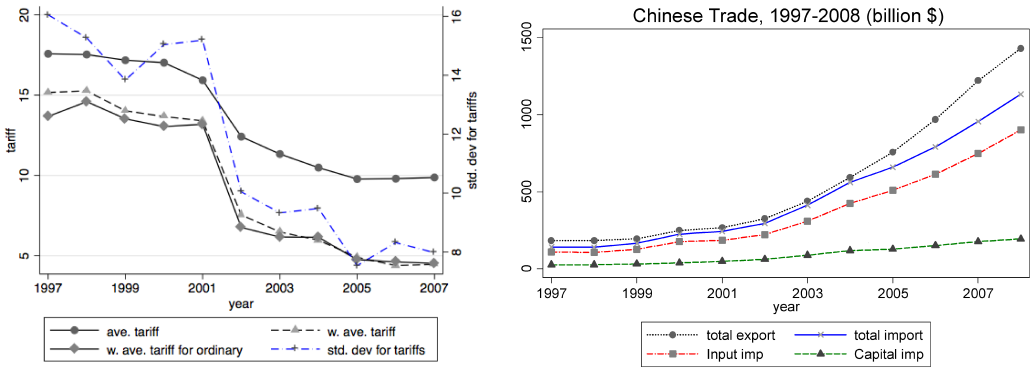

Figure 1: Tariff Reduction and China's Imports, 1997 - 2007

Data Source: Tariff data from WITS, and Chinese trade data from China Customs General Office.
Note: The mean and standard deviation of tariffs are calculated across six-digit HS products.

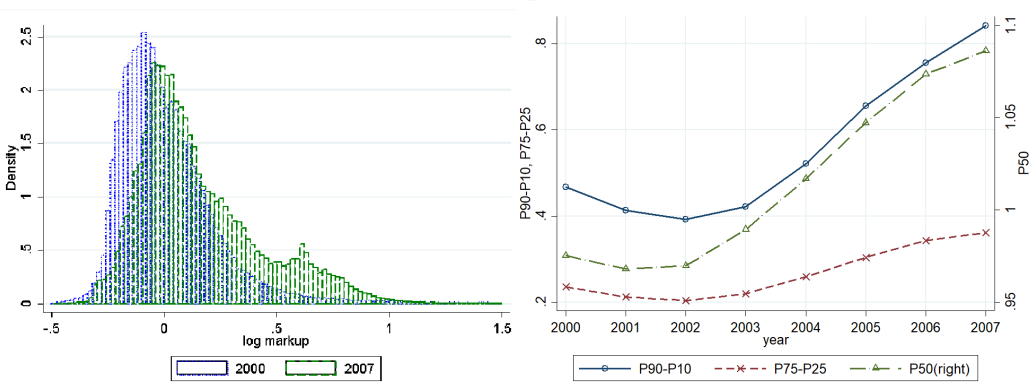

Figure 2: Evolution of Markup and Markup Dispersion

Data Source: authors' own calculation.

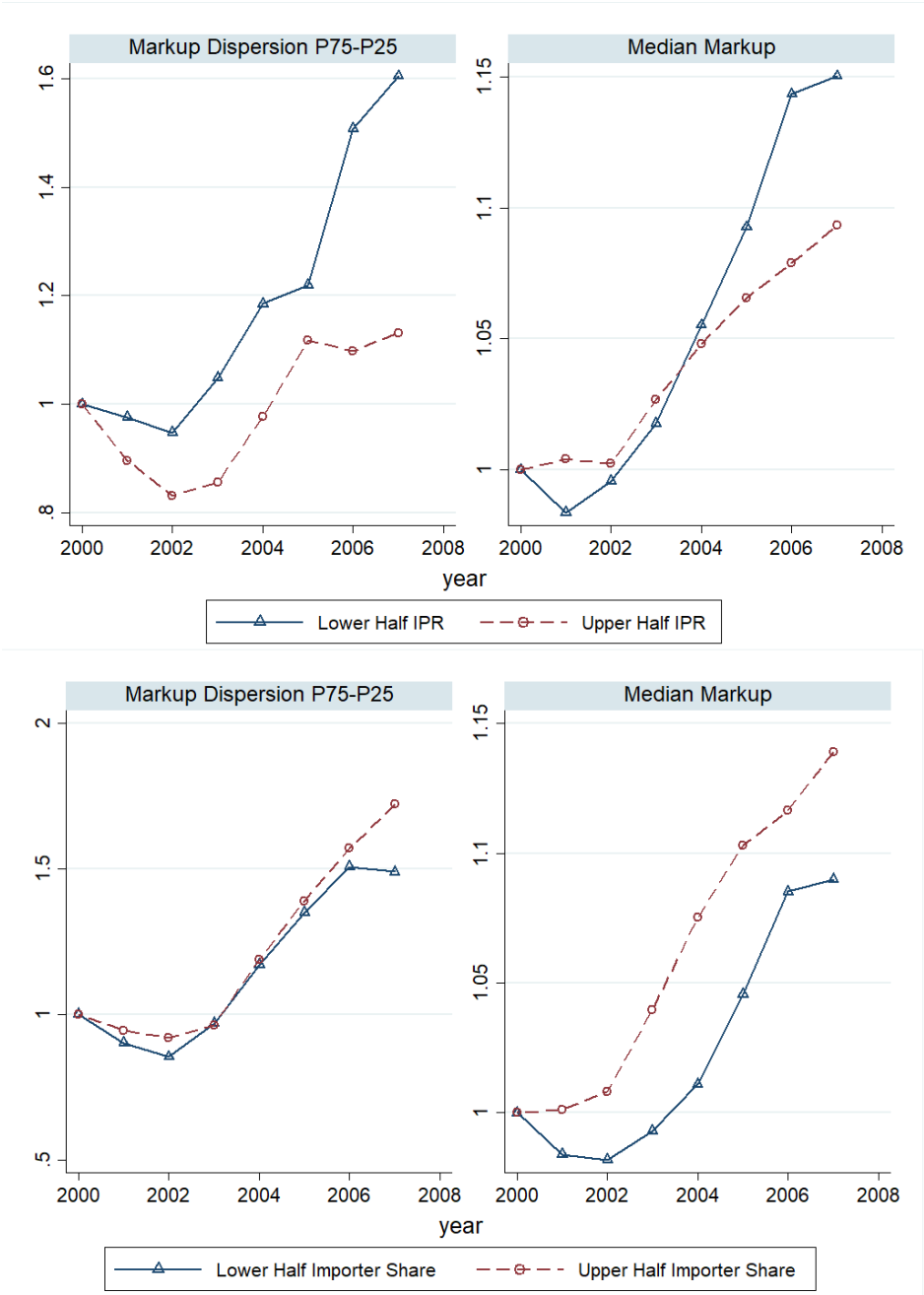

Figure 3: Changes in Markup and Markup dispersion: Groups of firms

Note: The upper panel shows evolution of markup and markup dispersion in industries with high v.s. low import penetration ratio. The lower panel shows evolution of markup and markup dispersion in industries with high v.s. low importer fraction. In each panel, the value in 2000 for both variables are normalized to 1.

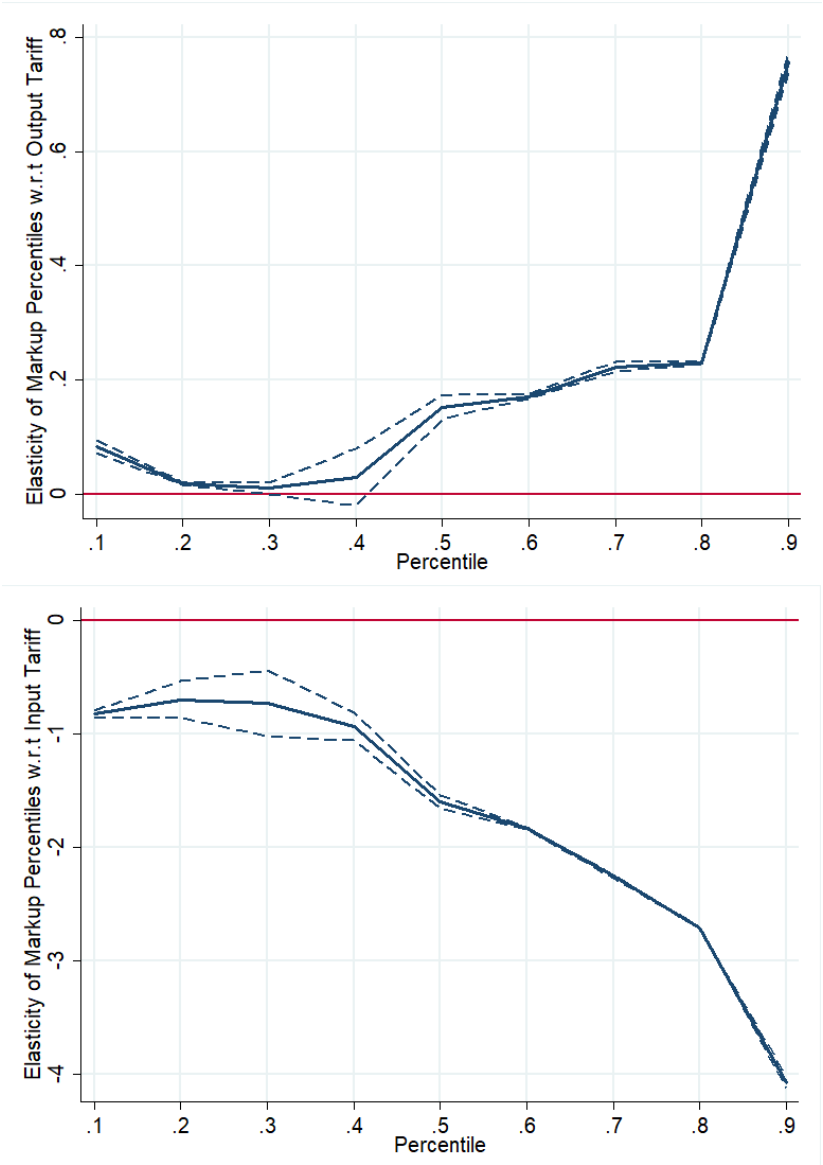

Figure 4: Coefficients in Panel Data Quantile Regression

Note: This figure shows the coefficients of output and input tariff in panel data quantile regression in Table 2, i.e. markup elasticity w.r.t output and input tariffs.

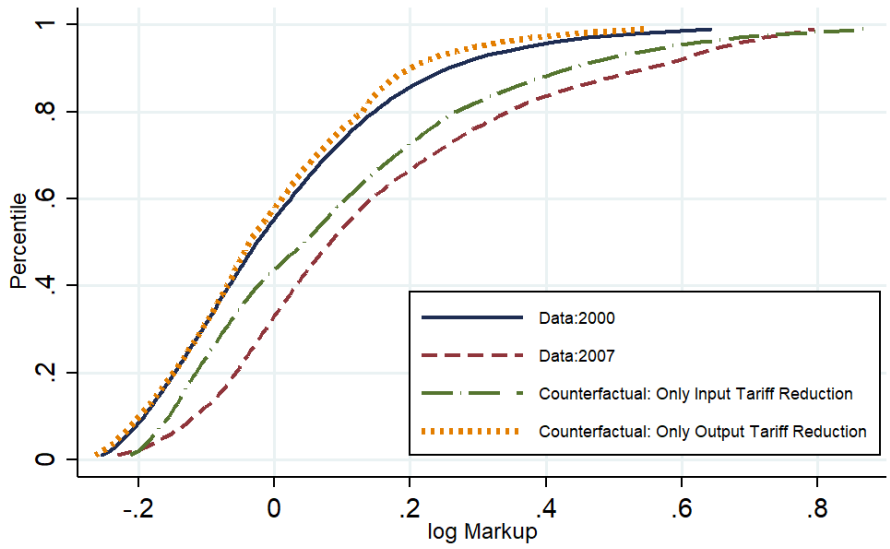

Figure 5: Counterfactual Cumulative Markup Distribution (based on PDQR results)

Note: This figure plots the counterfactual markup distribution based on the estimated coefficients in Figure 4, together with the actual markup distribution in 2000 and 2007.

Table 1: Descriptive Summary

Variable	Obs	Mean	Std. Dev.	Min	Max
A: Firm Characteristics (2000-2007)					
Markup	1,575,162	1.103	0.268	0.764	2.342
Export Dummy	1,575,162	0.288	0.453	0	1
Import Dummy	1,575,162	0.145	0.352	0	1
Age (in log)	1,575,162	1.968	0.862	0	4.615
TFP (in log)	1,575,162	1.415	0.456	-1.482	4.839
SOE dummy	1,575,162	0.090	0.287	0	1
Foreign Firm Dummy	1,575,162	0.217	0.412	0	1
B: Tariff at Industry Level (2000-2007)					
Input Tariff	568	0.080	0.042	0.022	0.327
Output Tariff	568	0.132	0.100	0.000	0.650
C: Industry Characteristics in 2000					
Import Penetration Ratio	71	0.097	0.112	0.000	0.505
Importer Fraction	71	0.152	0.127	0.013	0.543
C: Production Variables (2000-2007)					
Output/1000	1,608,402	76157.82	657008.60	17.147	2.03E+08
Material Input/1000	1,608,402	53547.36	483408.10	10	1.68E+08
Employment	1,608,402	253.84	923.06	11	1.88E+05
Real Capital/1000	1,608,402	26869.85	326224.00	0.625	9.74E+07

Note: Data from the ASIP dataset and the Custom Data. The number of manufacturing industries in the IO table is 71. The correlation coefficient of output tariff and input tariff is 0.79.

Table 2: Baseline Regression using Panel Data Quantile regression

	(1)	(2)	(3)	(4)	(5)
Percentile	10	25	50	75	90
Dependent Variable			log markup		
Input Tariff	-0.825***	-1.069***	-1.598***	-3.210***	-4.067***
	(0.0156)	(0.0731)	(0.0300)	(0.216)	(0.0280)
Output Tariff	0.0827***	0.109***	0.152***	0.340***	0.757***
	(0.00590)	(0.0196)	(0.0106)	(0.0511)	(0.00875)
FM	0.0263***	0.0246***	0.0189***	0.0397***	-0.0202***
	(0.000111)	(0.00376)	(0.000868)	(0.0121)	(0.00255)
FX	-0.00175***	-0.00369**	-0.0128***	0.00560*	-0.00848***
	(0.000508)	(0.00179)	(0.00125)	(0.00297)	(0.00247)
SOE	0.0253***	0.0312***	0.0593***	0.0885***	0.162***
	(0.000382)	(0.00150)	(0.00146)	(0.0151)	(0.00325)
FIE	0.00319***	0.0104***	0.0292***	0.0266***	0.0489***
	(0.000208)	(0.00272)	(0.000142)	(0.00956)	(0.000620)
TFP	-0.0650***	-0.0847***	-0.101***	-0.000571	0.00571***
	(0.000834)	(0.00211)	(0.00126)	(0.00810)	(0.00135)
Log Age	-0.00534***	-0.00248*	-0.00177***	-0.0105***	-0.00626***
	(0.000216)	(0.00133)	(0.0000773)	(0.00168)	(0.000232)
N	1575162	1575162	1575162	1575162	1575162

Note: Panel data quantile regression of markups on output tariff, input tariff, and control variables. Both output tariff and input tariff are measured at industry level. Control variables include firm age, exporter dummy (FX), importer dummy (FM), productivity (TFP), state-owned dummy and foreign firm dummy. All regressions include year dummies. Standard error in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Aggregate Changes and Counterfactuals

	Median	Mean	Variance
Data:2000	-0.0251	0.0078	0.0293
Data:2007	0.0827	0.1412	0.0553
Counterfactual: input tariff	0.0456	0.0884	0.0504
Counterfactual: output tariff	-0.0365	-0.009	0.0232
Contribution: input tariff	65.00%	60.40%	81.20%
Contribution: output tariff	-10.60%	-12.60%	-23.50%

Table 4: Mechanism: Interaction Terms

	(1)	(2)	(3)	(4)	(5)	(6)
Percentile	25	50	75	25	50	75
Dependent Variable			Log markup			
Input Tariff	-1.138***	-1.802***	-2.152***	0.0511***	-0.450***	-0.912***
	(0.00329)	(0.126)	(0.0150)	(0.00239)	(0.0103)	(0.228)
Output Tariff	-0.0854***	-0.00861	-0.0583***	-0.0744***	-0.113***	-0.254***
	(0.00171)	(0.0560)	(0.00447)	(0.00131)	(0.00166)	(0.0979)
Output Tariff × *IPR*	0.990***	0.482	0.171**	-1.670***	1.014***	2.507***
	(0.0133)	(0.302)	(0.0775)	(0.0178)	(0.0316)	(0.470)
IPR	-0.350***	-0.427***	-0.382***	-0.0246***	-0.338***	-0.788***
	(0.00195)	(0.0118)	(0.00851)	(0.00309)	(0.00128)	(0.0764)
Input Tariff × *IS*				-5.331***	-5.089***	-5.046***
				(0.0399)	(0.108)	(1.157)
IS				0.358***	0.367***	0.220
				(0.00349)	(0.00897)	(0.190)
Other Control	YES	YES	YES	YES	YES	YES
N	1575162	1575162	1575162	1575162	1575162	1575162

Note: Panel data quantile regression of markups on output tariff, input tariff, interaction term between import penetration ratio (IPR) and output tariff, importer fraction (IS) and input tariff, and control variables. Both output tariff and input tariff are measured at industry level. Other Control variables include firm age, exporter dummy (FX), importer dummy (FM), productivity (TFP), state-owned dummy and foreign firm dummy. All regressions include year dummies and non-additive firm fixed effect. Standard error in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Continuing Firms and Entrants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Continuing Sample			New Entrants			Above-3 years Sample		
Percentile	25	50	75	25	50	75	25	50	75
Dependent Variable	Log markup								
Input Tariff	-1.233***	-1.606***	-1.844***	-1.186***	-1.721**	-0.671	-1.210***	-2.211***	-2.467***
	(0.00287)	(0.00468)	(0.00208)	(0.303)	(0.725)	(1.298)	(0.0145)	(0.0336)	(0.0295)
Output Tariff	0.118***	0.161***	0.0163***	0.136	0.204	-0.217	0.125***	0.295***	0.229***
	(0.00101)	(0.00131)	(0.000771)	(0.158)	(0.365)	(0.553)	(0.00595)	(0.0114)	(0.0546)
Other Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	339976	339976	339976	430519	430519	430519	1310357	1310357	1310357

Note: Panel data quantile regression of markups on output tariff, input tariff, and control variables. Balance sample in Column 1-3, new entrants sample in Column 4-6, and firms who exist in no less than 3 years sample in Column 7-9. Both output tariff and input tariff are measured at industry level. Other Control variables include firm age, exporter dummy (FX), importer dummy (FM), productivity (TFP), state-owned dummy and foreign firm dummy. All regressions include year dummies and non-additive firm fixed effect. Standard error in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Control for FDI and Ownership Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Percentile	25	50	75	25	50	75
Dependent Variable			Log markup			
Input Tariff	-0.891***	-1.203***	-2.969***	-0.810***	-1.378***	-3.112***
	(0.00251)	(0.0196)	(0.107)	(0.00638)	(0.101)	(0.0914)
Output Tariff	0.0264***	0.0599**	0.561***	-0.0883***	0.0430*	0.517***
	(0.0024)	(0.0286)	(0.0569)	(0.00895)	(0.0239)	(0.0461)
Input Tariff × FIE				-0.606***	0.440	0.223
				(0.0246)	(0.321)	(0.209)
Output Tariff × FIE				0.126***	-0.567***	-0.630***
				(0.0193)	(0.159)	(0.108)
Input Tariff × SOE				0.754***	0.458***	1.215***
				(0.00405)	(0.0514)	(0.0375)
Output Tariff × SOE				-0.0781***	0.0163	-0.0484***
				(0.00443)	(0.0211)	(0.0172)
FDIsector	0.0146***	0.139***	0.0971***			
	(0.00478)	(0.0137)	(0.0162)			
Other Controls	YES	YES	YES	YES	YES	YES
N	1575162	1575162	1575162	1575162	1575162	1575162

Note: Panel data quantile regression of markups on output tariff, input tariff, and control variables. Both output tariff and input tariff are measured at industry level. In Column 1-3, we include Sectoral FDI equity share. In Column 4-6, we include interactions between tariffs and ownership dummies. Other Control variables include firm age, exporter dummy (FX), importer dummy (FM), productivity (TFP), state-owned dummy and foreign firm dummy. All regressions include year dummies and non-additive firm fixed effect. Standard error in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Non-Processing Firms

	(1)	(2)	(3)
Percentiles	25	50	75
Input tariff	-0.567***	-1.474***	-1.905***
	(0.00389)	(0.0116)	(0.0411)
Output tariff	-0.141***	0.0103***	0.213*
	(0.00191)	(0.000753)	(0.118)
Controls	YES	YES	YES
N	1528081	1528081	1528081

Note: Panel data quantile regression of markups on output tariff, input tariff, and control variables. Both output tariff and input tariff are measured at industry level. The regression only include non-processing firms. Other Control variables include firm age, exporter dummy (FX), importer dummy (FM), productivity (TFP), state-owned dummy and foreign firm dummy. All regressions include year dummies and non-additive firm fixed effect. Standard error in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.