Trade Liberalization, Labor Market Power, and Misallocation across Firms: Evidence from China's WTO Accession [*]

Enze Xie
Zhejiang University

Mingzhi Xu
Peking University

Miaojie Yu
Liaoning University

August 13, 2024

Abstract

This paper studies the impact of trade liberalization on the heterogeneity of labor market power among manufacturing firms, which is a potential source of misallocation. The model shows that heterogeneity of labor market power distorts the allocation of the factors of production, and the variance in the natural log of the markdown serves as a sufficient statistic to infer its negative impact on overall production efficiency. Using China's accession to the World Trade Organization (WTO) as a natural experiment, the empirical results suggest that lower input tariffs decrease the variance in the natural log of the markdown, which reflects the improvement in misallocation. In contrast, reductions in output tariffs have no significant effect.

Keywords: heterogeneous monopsony power, misallocation, trade liberalization, markdown distribution

JEL Codes: F12, F14, F16, J42

[*]Miaojie Yu is thankful for financial support from the National Social Science Foundation of China (Grant No.21VMG006), the National Nautral Science Fundation of China (Grant No.72073005 & No.72341017) and Beijing Outstanding Young Scientist Program. Mingzhi Xu is thankful for financial support from the Natural Science Foundation of China (Grant No.72322007). Enze Xie, School of Economics, Zhejiang University, Hangzhou, China, email: ezxie2019@nsd.pku.edu.cn; Mingzhi Xu, Institute of New Structural Economics, Peking University, Beijing, China, email: mingzhixu@nsd.pku.edu.cn; Miaojie Yu (*corresponding author*), Liaoning University, Shenyang, China, email: mjyu@lnu.edu.cn. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. The results and opinions presented in this paper do not represent the views of our institutions, or the countries they represent.

1 Introduction

A country's aggregate production efficiency does not rely solely on the average level of productivity among firms. Rather, it is also contingent upon the efficient distribution of production factors across firms. The presence of factor misallocation, which is an inefficient allocation of production factors, has garnered substantial attention as a significant source of welfare loss, as highlighted by Hsieh & Klenow (2009). The literature has primarily focused on the impacts of markups on misallocation, emphasizing that the dispersion in markups is the primary driver of aggregate output (Edmond et al., 2015; Peters, 2020). However, the misallocation of input factors, such as labor, has been relatively underexplored. This paper aims to address this gap in the literature by examining the distortionary impact of heterogeneous monopsony power in the labor market across Chinese firms on equilibrium factor allocation.[1] As emphasized by Atkin & Khandelwal (2020), widespread domestic distortions in developing countries can alter the impact of trade policy reform.[2] Motivated by the interplay between trade policy reform and domestic distortion, we aim to quantify the welfare effects associated with the reallocation of labor after China's accession into the World Trade Organization (WTO) in 2001, from the lens of imperfect competition in the labor market.

To analyze how heterogeneous monopsony power across firms leads to welfare consequences at the aggregate level, we construct a model with monopolistic competition in the product market and monopsonistic competition in the labor market. Built on Card et al. (2018), the model introduces heterogeneous monopsony power across firms, by assuming that workers' preference for a job is governed by a generalized extreme value distribution that has three layers, inspired by Fajgelbaum et al. (2011). The model shows that given the estimated parameters, the first and second moments of the industry distribution of monopsony power are *sufficient statistics* of the effect of imperfect competition in labor markets on the aggregate economy.

At the micro level, the theoretical results show that the firm-level monopsony power leads firms to produce less output, charge higher prices, use less input, substitute non-labor inputs for labor, and increase the marginal revenue product of labor (MRPL) and revenue-based total factor productivity (TFPR).[3] At the macro level, we find that heterogeneity in firm monopsony power leads to the misallocation of production factors and induces aggregate efficiency loss. These findings are similar to those of Hsieh & Klenow (2009), but distortions are endogenous in our model. Our model derives that the variance in the natural log of the markdown serves as a *sufficient statistic*, which we use to infer the overall efficiency of production at the national level. Our model also demonstrates that input trade liberalization is associated with a decrease in the heterogeneity of firms' labor market power, while output trade liberalization has the opposite association.

Next, we quantify the welfare effect associated with labor reallocation around the time when China joined the WTO in 2001. Using difference-in-differences (DID) regression, we explore the impact of trade liberalization on the variance of log markdown. Markdown, which is the ratio of the MRPL to the wage,

[1] For simplicity, monopsony power refers to firms market power in the labor market in the following, unless otherwise stated.
[2] Bai et al. (2024) even argue that the gains from trade turn negative with the existence of firm-level distortion.
[3] Appendix C presents the firm-level equilibrium results.

is estimated following Yeh et al. (2022). Following Brandt et al. (2017), we use industry-level input and output tariffs as proxies for trade liberalization. Using data from the Chinese Annual Survey of Industrial Firms (ASIF) for 1998-2007, the empirical evidence shows that lower input tariffs reduce the variance of log markdown on average, and reductions in firm markdowns are larger among firms with higher monopsony power. In contrast, reductions in output tariffs have no significant effect. The results suggest that input trade liberalization helps to mitigate misallocation in the labor market and improve aggregate production efficiency. Our empirical results are robust to alternative measures of markdown and different specifications.

This paper is related to three strands of literature. First, our work complements the literature on misallocation by identifying a novel source of misallocation, which is heterogeneous monopsony power. Previous work mainly focused on misallocation in the capital and the product markets (Edmond et al., 2023; Epifani & Gancia, 2011; Hsu et al., 2020; Midrigan & Xu, 2014; Peters, 2020).[4] The input market, especially the labor market, has received considerably less but increasing attention (Morlacco, 2019; Rabinovich & Wolthoff, 2022; Tortarolo & Zarate, 2018; Trottner, 2023). Bai & Cheng (2016) measure labor misallocation in China at the province level between 1980 and 2010. They find that the secondary sector's wage deviations from the MRPL contributed to labour misallocation, and opening to trade improved the allocation. Tortarolo & Zarate (2018) measures the the market power in the product and labor markets simultaneously. They find that the counterfactual of removing variable labor market power increases total factor productivity (TFP) by 2.5% across sectors. Trottner (2023) constructs a model of imperfect competition in output and factor markets with fixed costs, an endogeneous number of firms, and variable markups and markdowns. As emphasized by Trottner (2023), when markdowns or markups differ across producers, the market allocation becomes inefficient due to several distortions. The micro-level distributions of markups and markdowns shape the equilibrium's response to shocks, and abstracting from markdowns understates not only the overall welfare loss, but also the importance of the indirect efficiency effect. To complement the literature, in the spirit of Hsieh & Klenow (2009) and Trottner (2023), our model shows that firm heterogeneity in monopsony power in the labor market generates differentiation in MRPL, leads to misallocation across firms, and results in an efficiency loss.[5] Specifically, the variance in the log of markdown, captures the effect of misallocation.

Second, this paper is related to the literature on the impact of trade liberalization on labor market power.[6] With the revival of interest in imperfect competition in the labor market, dozens of papers have focused on the interaction between trade and imperfectly competitive labor markets.[7] Many papers investigate the impact

[4] Lu & Yu (2015) and Liu & Ma (2021) estimate the impact of tariff reduction during China's WTO accession on firms' markup and markup distribution and find that, output tariff liberalization reduces markup and markup dispersion, while input tariff liberalization has the opposite effect.

[5] Efficient allocation of production factors across firms can be achieved only if the marginal products of different firms are equivalent in a static model of production and demand. Any deviation incurs misallocation (Restuccia & Rogerson, 2008).

[6] Previous work mainly concentrated on studying the effect of trade liberalization on product market power, i.e., the markup (Brandt et al., 2017; De Loecker et al., 2016; Edmond et al., 2015; Fan et al., 2018; Levinsohn, 1993; Liu & Ma, 2021).

[7] The persistent decrease in the labor's share across countries (Dorn et al., 2017; Karabarbounis & Neiman, 2014), the stagnant wage growth (Gould, 2014), and high inequality within countries (Card et al., 2013) have made imperfect competition in the labor market to be the focus of a burgeoning research recently (Boal & Ransom, 1997; Manning, 2003a; Manning, 2003b).

of trade liberalization on firms' monopsony power per se (Ahsan & Mitra, 2014; Dobbelaere & Wiersma, 2020; Felix, 2021; Kondo et al., 2023; Macedoni & Tyazhelnikov, 2024; MacKenzie, 2021; Pham, 2023). Other papers focus on the impacts of import competition (Caselli et al., 2021; Mertens, 2020) and foreign direct investment (Lu et al., 2019) on labor market power. Previous work primarily focused on the impact of trade liberalization on firms' labor market power per se, while the heterogeneity of firms' labor market power and its welfare implications have been neglected. Our study demonstrates that input trade liberalization reduces the heterogeneity of labor market power across firms and alleviates misallocation, thereby serving as an additional channel for the gains from trade. Specifically, our work reveals two novel mechanisms through which trade liberalization exerts a heterogeneous impact on firms' labor market power: firms' intermediate input intensity and employment composition in terms of skilled and unskilled labor.

Third, this paper provides a model that characterizes firms' heterogeneous monopsony power in the labor market with good tractability. Manning (2021) shows that researchers often impose imperfect competition in the labor market in one of two ways, search frictions (Burdett & Mortensen, 1998; Wu, 2020) or preference heterogeneity (or job idiosyncrasy) (Card et al., 2018; Manning, 2003b). In the trade literature, there are also two types of models that characterize labor market power, oligopsonistic (Macedoni & Tyazhelnikov, 2024) and monopsonistic (Egger et al., 2021; Jha & Rodriguez-Lopez, 2021; Macedoni, 2021). In the monopsonistic model, the small-firm setting implies a constant monopsony power that does not vary across firms (Jha & Rodriguez-Lopez, 2021), while the big-firm setting implies the opposite (Brooks et al., 2021). The oligopsonistic model is also a big-firm setting, which generates oligopsony power that is positively correlated with firm size, but at the expense of losing tractability. Inspired by Fajgelbaum et al. (2011) and Card et al. (2018), we build a three-tier nested demand structure with a monopsonistic model in a small-firm setting to characterize firm-level variable monopsony power with good tractability.

The remainder of the paper proceeds as follows. Section 2 presents the theoretically analysis. Section 3 provides background information on the Chinese labor market. Section 4 offers an overview of the data, the background of China's WTO accession, and the estimation strategy for the key variables in our regressions. Section 5 presents the empirical specification and results. Section 6 concludes.

2 Theoretical Analysis

2.1 Theoretical Model

When firms compete with each other in an imperfectly competitive labor market, they are no longer price takers in the labor market but have wage-setting power, that is, monopsony power. In this section, we build a model to introduce heterogeneous monopsony power and characterize its impact on firms' behavior and the aggregate economy. The economy is populated by L units of consumers-workers. Each consumer is endowed with one unit of labor, and the supply of labor is inelastic.

2.1.1 Consumer Preferences and Labor Supply

The indirect utility of consumer i working in manufacturing industry s, firm j, and occupation o is

$$u_{isjo} = \ln(w_{sjo}) + \epsilon_{isjo} \tag{1}$$

where w_{sjo} denotes wages. The idiosyncratic additive term, ϵ_{isjo}, captures the other attributes of the job (such as relationships with colleagues), which consumers evaluate differently. The error term, ϵ, is assumed to be distributed independently across consumers according to a generalized extreme value distribution, $\mathrm{G}(\epsilon)$

$$G_\epsilon(\boldsymbol{\epsilon}) = \exp\left\{ -\left(\sum_{s\in S} \left[\sum_{j\in M_s} \left(\sum_{o\in M_j} \exp\left(-\epsilon_{sjo}/\theta_j\right) \right)^{\theta_j/\theta_s} \right]^{\theta_s/\theta} \right)^{\theta} \right\} \tag{2}$$

with $\theta_s \in (0,1)$ for all $s \in S$ and $\theta_j \in (0,1)$ for all $j \in M_s$ and $\theta > 0$, where S indexes the finite set of industries; and M_s and M_j denote the total number of firms in industry s and the total number of occupations in firm j, respectively. Consumers choose the industry, firm, and occupation in sequence, to obtain the highest utility. The probability of consumer i working in occupation o, firm j, and industry s is

$$\Pr\Big(\underset{s\in S, j\in M_s, o\in M_j}{\arg\max} \; u_{isjo} = s, j, o \Big) = \eta_{o|j} \cdot \eta_{j|s} \cdot \eta_s, \; \forall o \in M_j, j \in M_s, s \in S \tag{3}$$

where $\eta_{o|j}$, $\eta_{j|s}$, and η_s are the probability of consumer i choosing to work in occupation o conditional on working in firm j, the probability of consumer i choosing to work in firm j conditional on working in industry s, and the probability of consumer i choosing to work in industry s, respectively.

As a result, the probability of consumer i choosing to work in occupation o, firm j, and industry s is

$$\Pr\Big(\underset{s\in S, j\in M_s, o\in M_j}{\arg\max} \; u_{isjo} = s, j, o \Big) = \lambda_{sj} e^{ln(w_{sjo})/\theta_j} \tag{4}$$

where $\lambda_{sj} = \eta_s \eta_{j|s} \frac{1}{\sum_{k\in M_j} e^{ln(w_{sjk})/\theta_j}}$, λ_{sj} is common to all occupations within industry s and firm j. The labor supply curve for each occupation is derived by multiplying the probability and total labor supply

$$l_{sjo} = (L\lambda_{sj}) e^{ln(w_{sjo})/\theta_j} \tag{5}$$

Equation (5) shows that for each occupation, firms face an upward-sloping labor supply curve. Following Manning (2003a), we use markdown ψ to measure firms' monopsony power, defined as the ratio of the MRPL to the wage. Using the labor supply function in equation (5), the occupation-level markdown is

$$\psi_{sjo} = 1 + \frac{\partial w_{sjo}}{\partial l_{sjo}} \frac{l_{sjo}}{w_{sjo}} = 1 + \theta_j = \psi_{sj} \tag{6}$$

Equation (6) implies that the markdown is variable across firms but constant within firms. As noted by Fajgelbaum et al. (2011), θ_j is known as the dissimilarity parameter, which measures the degree of heterogeneity in workers' preferences for different occupations provided by individual firm j. Consequently, equation (6) shows that greater heterogeneity in preferences for different occupations within a firm gives the firm greater monopsony power. The intuition is that, from the perspective of the worker, the perceived heterogeneity in the nonpecuniary rewards of different occupations within the firm increases with θ_j. Workers are more likely to apply for the occupation with the highest value of ϵ_{sjo}, which in turn gives firms greater monopsony power over each occupation. On the other hand, from the perspective of firms, Booth et al. (2000) emphasize that worker heterogeneity affects the tasks that firms conduct. Firms with more heterogeneous occupations conduct more complex tasks and avoid fierce competition; thus, they have greater monopsony power over their workers. Fox (2010) stresses that firms should only hire workers who have a great nonpecuniary desire to work and then compress the wage below their MRPL to achieve higher profits. Workers' idiosyncratic preferences are unobservable for firms, but when workers choose a specific occupation, their preferences are revealed. Hence, firms have an incentive to expand the scope of occupations to take advantage of workers' heterogeneous preferences and compress wages to the largest extent.[8]

2.1.2 Production

The final product Q is produced by a representative firm in the competitive final goods market. This firm combines the output Q_s of S manufacturing industries using Cobb-Douglas production technology

$$Q = \prod_{s=1}^{S} \mathrm{Q_s^{\alpha_s}}, \text{where } \alpha_s \in (0,1),\ \forall s \in S, \sum_{s=1}^{S} \alpha_s = 1 \tag{7}$$

Cost minimization implies that $\mathrm{P_s Q_s} = \alpha_s \mathrm{PQ}\ (\forall s \in S)$. We make the final product Q the numeraire, and thus $P \equiv 1$. Furthermore, within each industry s, there exists a number of firms, denoted by M_s.[9] Each firm produces a variety, and varieties are combined to yield the industry-level output, according to a constant elasticity of substitution aggregation

$$\mathrm{Q_s} = \Big(\sum_{j \in M_s} q_{sj}^{\rho_s}\Big)^{\frac{1}{\rho_s}}, \rho_s \in (0,1) \tag{8}$$

where ρ_s governs the elasticity of substitution between different varieties that vary across industries. Finally, we assume a Cobb-Douglas production function for each firm within the industry

$$q_{sj} = \varphi_{sj} m_{sj}^{\beta_s} l_{sj}^{1-\beta_s}, \text{where } \beta_s \in (0,1) \tag{9}$$

[8] A similar story exists in the product market. Macedoni et al. (2020) show that in a model with heterogeneous consumers, consumer heterogeneity increases markups and makes markups differ across products.

[9] The firm dynamic is shut down here, and hence M_s is exogenously given.

where φ_{sj} is the Hicks-neutral TFP. The variable m_{sj} denotes other production factors, such as intermediate inputs. For convenience, we assume that firms imported all intermediate input from abroad. The variable l_{sj} indexes the composite labor, which is combined according to Cobb-Douglas aggregation by assumption

$$l_{sj} = \prod_{o=1}^{M_j} (l_{sjo})^{\gamma_o}, \text{where } \gamma_o \in (0,1),\ \forall o \in M_j, \sum_{o=1}^{M_j} \gamma_o = 1 \tag{10}$$

The labor structure implies that firm-level markdown is the Cobb-Douglas aggregation of occupation-level markdowns, which is in line with equation (6)

$$\psi_{sj} = \prod_{o=1}^{M_j} (\psi_{sjo})^{\gamma_o} = \prod_{o=1}^{M_j} (1+\theta_j)^{\gamma_o} = (1+\theta_j)^{\sum_{o=1}^{M_j}\gamma_o} = 1+\theta_j = \psi_{sjo} \tag{11}$$

2.1.3 Misallocation and Efficiency Loss

We can express aggregate output as a function of l_s, m_s, and industry-level TFP:

$$Q = \prod_{s=1}^{S} {Q_s}^{\alpha_s} = \prod_{s=1}^{S} \left(\text{TFP}_s {m_s}^{\beta_s} {l_s}^{1-\beta_s}\right)^{\alpha_s} \tag{12}$$

As a result, we can express industry-level TFP as follows:

$$\text{TFP}_s = \frac{Q_s}{{m_s}^{\beta_s} {l_s}^{1-\beta_s}} \tag{13}$$

Following the derivation of Hsieh & Klenow (2009), industry-level TFP is given by:

$$\text{TFP}_s = \left[\sum_{j \in M_s} {\varphi_{sj}}^{\frac{\rho_s}{1-\rho_s}} \left(\frac{\overline{\text{MRPL}_s}}{\text{MRPL}_{sj}}\right)^{\frac{(1-\beta_s)\rho_s}{1-\rho_s}}\right]^{\frac{1-\rho_s}{\rho_s}} \tag{14}$$

Equation (14) reveals that industry-level TFP is homogeneous of degree zero in monopsony power. The average level of monopsony power has no impact on industry-level TFP.

Following Hsieh & Klenow (2009), we assume that φ_{sj}, ψ_{sj}, and w_{sj} are jointly log-normally distributed.[10] The following is a simple closed-form expression for industry-level aggregate TFP:[11]

$$\log \text{TFP}_s = \log\left(\sum_{j \in M_s} {\varphi_{sj}}^{\frac{\rho_s}{1-\rho_s}}\right)^{\frac{1-\rho_s}{\rho_s}} - \Gamma_{1s} \text{var} \log \psi_{sj} \tag{15}$$

[10] Firm-level wage is the Cobb-Douglas aggregation of occupation-level wage, $w_{sj} = \prod_{o=1}^{M_j} \left(\frac{w_{sjo}}{\gamma_o}\right)^{\gamma_o} = \frac{1}{\gamma_o}\left(\frac{1}{L\lambda_{sj}}\right)^{\theta_j} {l_{sj}}^{\theta_j}$

[11] For the details on the derivation, please refer to Appendix D.

where:

$$\Gamma_{1s} = \frac{(\beta_s \rho_s - 1)(\beta_s - 1)}{2(1-\rho_s)} > 0$$

The negative effect of monopsony power on industry-level TFP can be summarized as the variance of log markdown.[12] The heterogeneity of firms' markdowns incurs an efficiency loss. Our results complement those of Hsieh & Klenow (2009) by endogenizing the distortion. In Hsieh & Klenow (2009), the distortion is exogenously given, and firms are price takers in the input market. In our model, the distortion is endogenous, stemming from firms' heterogeneous monopsony power in the labor market. The intuition is that without dispersion in firm-level markdown, the allocation of labor across different firms is completely determined by productivity. In contrast, when we introduce heterogeneous monopsony power across firms, the allocation of the factors of production is not only determined by productivity, but also distorted by firms' monopsony power, which gives rise to misallocation and loss of production efficiency.

Proposition 1. *Firms' heterogeneous monopsony power induces an intra-industry misallocation and results in a TFP loss. The variance in log markdown serves as a sufficient statistic of the negative impact of the heterogeneity of firms' monopsony power on total productivity.*

2.1.4 Impact of Trade Policy

Trade policy is modeled by the output tariff τ and input tariff t. The firm's profit maximization problem can be expressed alternatively as the following:

$$\max_{m_{sj}, l_{sj}} \tau p_{sj}(q_{sj}) q_{sj} - w_{sj}(l_{sj}) l_{sj} - t w^m m_{sj} \tag{16}$$

where $t > 1$ is the input tariff, and $\tau > 1$ is the output tariff. Following the same algebra, we can infer that:

$$\text{var} \log \psi_{sj} = \alpha_1 lnt + \alpha_2 ln\tau + \frac{1}{\Gamma_{1s}} \log \Big(\sum_{j \in M_s} {\varphi_{sj}}^{\frac{\rho_s}{1-\rho_s}} \Big)^{\frac{1-\rho_s}{\rho_s}} - \frac{1}{\Gamma_{1s}} \log \text{TFP}_s \tag{17}$$

where $\alpha_1 = \frac{1}{\Gamma_{1s}} \frac{\beta_s}{1-\rho_s} > 0$, which implies that input tariff reduction is associated with a decrease in markdown heterogeneity within the industry, while $\alpha_2 = \frac{-1}{\Gamma_{1s}} \frac{1}{1-\rho_s} < 0$, which implies that output tariff reduction is associated with an increase in markdown heterogeneity within the industry.

Proposition 2. *Input trade liberalization is associated with a reduction in the heterogeneity of firms' labor market power, and output trade liberalization is associated with an increase in the heterogeneity of firms' labor market power.*

[12] Since the industrial outputs combine with each other according to a Cobb-Douglas aggregation, log TFP is the weighted average of log TFP_s, i.e., $\log \text{TFP} = \sum_{s=1}^{S} \alpha_s \log \text{TFP}_s$. Hence, proposition 1 applies to national-level productivity as well.

2.2 Conceptual Framework

The model has limitations in explaining the heterogeneous impact of trade liberalization on firms' labor market power per se. However, the burgeoning research on trade and labor market power offers valuable insights. This section delineates the possible channels through which trade liberalization can differentially affect firms' labor market power, drawing on established literature to supplement our analysis.

This subsection is mainly based on Kondo et al. (2023) and Pham (2023). Kondo et al. (2023) propose a model in which firms' labor market power is endogenously determined by the response of the firm-level and the aggregate labor supply elasticity to the input tariff reduction. When the intermediate input price decreases due to an input tariff reduction and increase in the supply of labor is sufficient, the number of operating firms increases and, consequently, their labor market power decreases. Pham (2023) emphasizes the extensive margin of firm entry and exit as the main channel. Output tariff reduction intensifies product market competition, reduces firms' profits, and induces exit, while input tariff reduction lowers production costs, makes more firms profitable enough to cover the fixed costs, and induces entry.[13]

Another way in which trade liberalization impacts firms' labor market power is by changing firms' labor composition in terms of skilled labor and unskilled labor. In China, skilled labor is more exposed to exploitation by firms, compared to unskilled labor, which is consistent with the literature (Fan et al., 2020; Kondo et al., 2023). Pham (2023) also shows that industries with larger high-skill employment ratios are associated with larger markdowns in the labor market. Using ASIF data from 2004 with additional information on workers' education backgrounds, the firm-level regression results in Table B.2 in Appendix B also confirm that a higher skilled labor ratio is correlated with higher markdown in the labor market.[14] Table B.2 in Appendix B shows that input tariff liberalization is associated with less use of skilled labor and hence a reduction in firms' markdowns while output tariff liberalization does the opposite.

In terms of heterogeneous impacts, Pham (2023) emphasizes that the impact of input trade liberalization on individual firms' labor demand relies on firms' input factor ratio, that is, the usage of intermediate inputs relative to other production factors.[15] Firms that use intermediate inputs intensively enjoy a greater cost-saving effect due to input tariff reduction. Moreover, they will use relatively more intermediate inputs during expansionary periods due to the increasing marginal cost of labor stemming from a steeper upward-sloping labor supply curve. As a result, the employment share of these firms in the local labor market decreases,

[13]Moreover, Macedoni & Tyazhelnikov (2024) highlight the interplay between firms' labor market power and product market power and suggest that intermediate input market integration will reduce firms' oligopsony power, induce exit, and increase the oligopoly power of the remaining firms. The opposite directions of market power response in the product market and labor market are well founded in the literature (Damoah, 2021; Pham, 2023).

[14]Beyond China, Lee (2020) estimates the labor supply elasticity for Brazil, Canada, India, Mexico and the United States and finds that better-educated workers tend to have lower labor supply elasticities and are more exposed to the monopsony power. Kusaka (2023) uses data on manufacturing firms in Colombia and finds that high-skilled labor is more exposed to monopsony power.

[15]Appendix C presents the firm-level equilibrium analysis and finds that firms with greater labor market power will use relatively more intermediate inputs than other factors. Table B.3 in Appendix B confirms the positive relationship between firms' intermediate input-labor ratio and markdowns within firms and across firms within the same local labor market.

leading to a reduction in firms' labor market power.

In conclusion, the theoretical analysis demonstrates that input tariff reduction is associated with a decrease in firms' labor market power, while output tariff reduction has the opposite effect. Firm's dynamics and production structure serve as important mechanisms underlying these effects.

3 Institutional Background of the Chinese Labor Market

Since the reform and opening up in 1978, China has gradually shifted from a centrally planned economy under administrative directives to a decentralized, market-based economy, which has brought structural change to many facets of the country's economy and society. The prominent features of the structural change include but are not limited to migration from rural area to the urban areas, privatization of the state sector, and development of the trade union and labor protection regulatory framework (Lee et al., 2009; Yao & Zhong, 2013), in addition to the trade liberalization, which is the focus of this paper.

To provide a full picture of the Chinese labor market, several aspects require special attention and are discussed in detail. Overall, labor mobility is restricted, labor protection is weak, and labor unions is kind of symbolic. These aspects all allow space for firms' labor market power, which serves as the foundation for evaluating the impact of trade liberalization on the level and distribution of firms' labor market power.

3.1 Development of Trade Unions

Along with the structural change in China during the period of opening up, income inequality became more severe and raised social problems. Meanwhile, the unbalanced bargaining power between employers and workers, due to weak labor protection institutions and regulations, became a substantial challenge to economic development and social stability. Figure 1 shows that during our sample period, there was a steady increase in the number of labor dispute cases accepted by labor dispute arbitration committees.

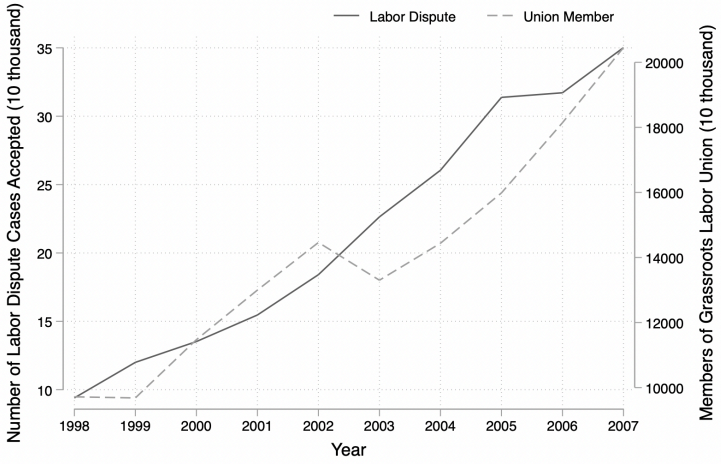

Figure 1: Labor Dispute Cases and Union Membership, 1998-2007

To mitigate the labor disputes, reduce strikes and social unrest, and control unionization, the goal of "*building a harmonious society*" was proposed, and trade unions played an important role in harmonizing industrial relations. With support from the government and led by the All-China Federation of Trade Unions, there was a drastic expansion of trade union membership, as shown in Figure 1.[16]

Compared with trade unions in other countries, the trade unions in China have two particular characteristics. (1) Unions have multiple purposes and functions, including maintaining social stability, helping with corporate management and governance, protecting workers' rights, bargaining with employers, mitigating labor disputes, providing financial support to workers in difficulty, and providing entertainment. (2) There are differences among the unions in terms of their dependence on the state, independence from employers and management, and bargaining power, which result in different organizational forms and functions.

Since the unions differ from each other a lot, the effects of unions in China are mixed. Several surveys reveal that workers' satisfaction with trade unions is very low (Liu, 2010), although some papers find that the trade unions help in promoting workers' interests (Ge, 2014; Lu et al., 2010; Yao & Zhong, 2013).

The ASIF data from 2004 provides information on the unions. Table 1 supports the view that union involvement can suppress firms' labor market power. However, only 45% of firms have a union, and the union's average expenditure is fairly low.

Table 1: Impact of Unions on Firms' Markdowns

Dependent Variables ln(Markdown)	(1)	(2)	(3)
Union Status	-0.350***		
	(0.013)		
Union Ratio		-0.339***	
		(0.018)	
Ln(Union Expenditure)			-0.135***
			(0.005)
Control	Yes	Yes	Yes
CIC-4 FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	241,587	237,413	239,558
Adjusted R^2	0.474	0.473	0.494

Note: Robust standard errors clustered at the CIC 2-digit level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. The control variables include total factor productivity (in log), total output (in log), capital-labor ratio (in log), and wage per capita (in log). Union Status takes the value of one if the firm has a union and zero if the opposite. Union Ratio is measured by the share of workers involved in the union.

In sum, the trade unions in China depend on the government politically and on the firms financially. The unions serve as an intermediate buffer between the government, workers, and firms, which has varying, overall

[16]The drop of union members in 2003 was due to a change in statistical caliberation. As a result, the number of workers in unions increased during our sample period.

effective but limited effects in protecting workers' interests. The role of trade unions is kind of symbolic and weak, which provides space for firms to exert labor market power and alleviates the endogeneity concern about tariffs, stemming from the "protection for sale" literature (Chen et al., 2017).[17]

3.2 Development of the Framework for Labor Protection Regulation

To meet the goals of "*building a harmonious society*" and "*pursuing progress in law-based governance,*" several laws and regulations were issued to balance the bargaining power between employers and employees.

Table 2: Relevant Laws and Regulations on Labor Relations

Classification	Document Name	Effective Date	Issuing Authority
Trade Union	Notice of The General Office of the State Council on In-depth Implementation of the Trade Union Law and Support for Trade Union Work	2004/12/15	GOSC
	Trade Union Law of the People's Republic of China (2001 Amendment)	2001/10/27	SCNPC
	The Trade Union Law of the People's Republic of China	1992/4/3	NPC
Collective Bargaining/Contract	Opinions of MLSS, ACFTU, CEC and CEDA on Carrying out Regional Industrial Collective Consultation Work	2006/8/17	MLSS ACFTU CEC CEDA
	Notice of the MLSS and ACFTU on Further Promoting Collective Wage Consultation	2005/2/6	MLSS ACFTU
	Notice of the MLSS, ACFTU, CEC and CEDA on Implementing the Provisions on Collective Contracts	2004/9/23	MLSS ACFTU CEC CEDA
	Provisions on Collective Contracts	2004/5/1	MLSS
	Notice of the MLSS and Other Four departments on Further Implementing the System of Equal Consultation and Collective Contract	2001/11/14	MLSS
	Trial Measures for Collective Wage Negotiation	2000/11/8	MLSS
Labor Disputes	Several Opinions of the ACFTU on Further Strengthening the Mediation of Labor Disputes	2007/6/11	ACFTU
	Notice of the MLSS, ACFTU, CEC and CEDA on Further Strengthening the Mediation of Labor Disputes	2005/8/4	MLSS ACFTU CEC CEDA
	Notice of the MLSS on Further Strengthening the Handling of Labor Disputes	2001/11/14	MLSS
	Interpretation of the SPC on Several Issues Concerning the Application of Law in the Trial of Labor Dispute Cases	2001/4/16	SPC
Minimum Wage	Guideline of the General Office of the ACFTU on Promoting the Increase and Implementation of Minimum Wage Standards	2006/5/19	ACFTU
	Provisions on Minimum Wages	2004/1/20	MLSS

Note: The contents of the table are summarized at https://www.pkulaw.com, which contains rich information on the official legal documents. ACFTU = All-China Federation of Trade Unions; CEC = China Enterprise Confederation; CEDA = China Enterprise Directors Association; GOSC = General Office of the State Council; MLSS = Ministry of Labour and Social Security; NPC = National People's Congress; SCNPC = Standing Committee of the National People's Congress; SPC = The Supreme People's Court.

[17]Table B.1 compares the mean values of input and output tariffs between industries with high union coverage and low union coverage, using the 2004 ASIF data. The results show that there is no significant difference in tariffs between industries in which trade unions play a larger role and those with less union enrollment. This comparison shows that there are no significant differences in tariff levels based on union coverage, ensuring that our empirical results are not biased by the impact of trade unions.

Table 2 summarizes the relevant labor relation laws and regulations proposed around our sample period, covering trade unions, collective bargaining (wage negotiation), collective contracts, labor dispute mediation, and the minimum wage. Despite the increasing number of pro-labor laws and regulations, the contents covered in the regulations are somewhat vague or the standard is too low; therefore, they fail to add many additional or enough benefits for workers (Lee et al., 2009; Liu, 2010).[18]

3.3 Rural-Urban Migration

The structure of the rural-urban dichotomy is a prominent characteristic of the Chinese economy. The rural-urban separation is due to the enforcement of the household registration system, "hukou". Job opportunities, public services, and other social benefits are bounded to people's "hukou", which makes migrants moving from rural to urban areas vulnerable. Compared with native urban residents, migrants: (1) are often employed in the informal sector or take jobs that urban residents do not want to take; (2) have limited access to public services and work benefits; and (3) are often unskilled, less educated, and have relatively low levels of human capital.[19] Brzezinska (2021) finds that relaxation of the geographical labor mobility restriction in China suppressed firms' monopsony power over their workers. However, relaxation of the labor mobility restriction has been sluggish; thus, firms are more powerful compared to their workers.

3.4 Privatization of the State Sector

To cope with the loss-generating state-owned enterprises (SOEs) and prepare for joining the WTO, the Chinese government introduced the state sector reform in the mid-1990s. According to the National Bureau of Statistics, China laid off 30 million SOE workers between 1998 and 2005. The SOE reform dramatically expanded the private sector and fundamentally influenced the labor market. Compared with private firms, SOEs have three particular characteristics. (1) SOEs take on the role of social responsibility in providing public services such as hospitals, fire-fighting systems, and education. Specifically, SOEs are responsible for maintaining employment stability (Bai et al., 2006), which makes them prone to overstaffing, shirking, and

[18]Figure B2 shows that the average wage of manufacturing firms in our data is higher than the minimum wage. This indicates that most firms are not constrained by minimum wage regulations. This reduces the likelihood that our results are influenced by changes in the minimum wage, thereby alleviating concerns about it being a confounding factor. The ASIF data does not provide information on the collective bargaining behavior of workers within firms. Fortunately, Zhan et al. (2012) utilize survey data from firms investigated and provided by the World Bank and the China Center for Economic Research at Peking University in 2005. They find that collective bargaining in China is not pervasive. The survey examines 1,268 firms in Beijing, Changchun, Dandong, Hangzhou, and other cities in China, primarily focusing on manufacturing industries. Among these firms, only 346 have collective wage agreements, accounting for just 27.3% of the firms. Considering that 2005 is near the end of our sample period and collective bargaining is on the rise, we can infer that the prevalence of collective bargaining was quite limited around the time of WTO accession. More importantly, Zhan et al. (2012) find that collective bargaining has no significant effect on improving wages for workers or managers. The only significant positive effects are observed in high-wage state-owned enterprises (SOEs). In our regression analysis, we also control for SOE reform. Consequently, our empirical results are not threatened by the influence of collective bargaining.

[19]Meng (2012) provides a detailed description of and statistics on the characteristics of migrants.

being less productive. (2) SOEs have limited autonomy in the labor market. Lifetime jobs are assigned to workers. Firms are not allowed to hire and fire, and wages are determined based on administration instead of market competition (Meng, 2012). (3) SOEs enjoy the market privilege represented by soft budget constraints through subsidies, taxation, credit, and price regulation. They also have easier access to land, capital, and production factors other than labor (Chen et al., 2019), which makes them less motivated to optimize labor demand to make profits.

In sum, compared with SOEs, private firms have greater monopsony power. After the SOEs' were privatized, firms were more likely to be solely profit-driven, which resulted in reducing redundant labor and suppressing wages or wage growth. Dan & Yi (2017)'s work verify this, as they find that SOE reform reduced workers' bargaining power, based on data on Chinese manufacturing firms data between 1998 and 2007.

4 Data, Background, and Measurement of Key Variables

4.1 Data and Processing

To quantify the welfare impact associated with labor reallocation after China joined the WTO, we rely on the following two large panel data sets: tariff data and firm-level production data. Tariff data can be accessed directly from Brandt et al. (2017), who provide input and output tariffs at the 4-digit level of the China Industrial Classification (CIC-4).[20] The firm-level production data are from the ASIF collected by China's National Bureau of Statistics. The ASIF data have been widely used in academic research (Brandt et al., 2012; Yu, 2015). The ASIF data covers all SOEs and non-SOEs with annual sales greater than RMB 5 million (US$ 770,000). Complete information on the three major accounting statements (i.e., balance sheet, profit and loss account, and cash flow statement) is also available. Although the data set contains rich information, some of the samples are still noisy and therefore misleading (Brandt et al., 2014). Following Ahn et al. (2011), Cai & Liu (2009), Brandt et al. (2014) and Yu (2015), we omit outliers and trade intermediaries and only retain manufacturing industry firms. Appendix A shows the details.

4.2 Background: China's WTO Accession

4.2.1 Import Tariff Reduction and DID Setup

In 1986, China applied to the General Agreement on Tariffs and Trade to restore its status as a contracting party. After 15 years of long negotiations, China finally rejoined the WTO on December 11, 2001. To join the WTO, China had to carry out substantial unilateral trade liberalization reforms. Figure 2 shows the simple averages and 25th and 75th percentiles of the input and output tariffs at the CIC-4 industry level from 1992 to 2007. From 1992 to 1997, China's input and output tariffs both showed a downward trend. The average input tariff fell from 26.9% to 11.4%, and the average output tariff fell from 43.7% to 17.9%.

[20]Both the input tariff and the output tariff are import tariffs. For illustration convenience, we omit the word "import".

From 1997 to 2001, the input and output tariffs remained stable. After joining the WTO in 2001, both tariffs showed a downward trend, and after 2005, both tariffs remained stable.

Figure 2 also shows that the input tariff is lower than the output tariff, but the gap between the two has decreased over time. Meanwhile, the reduction in the difference between the 25th percentile and 75th percentiles over the years indicates that the reduction in the tariffs has been universal across industries, which could provide evidence of an exogenous source of tariff changes (Pham, 2023).

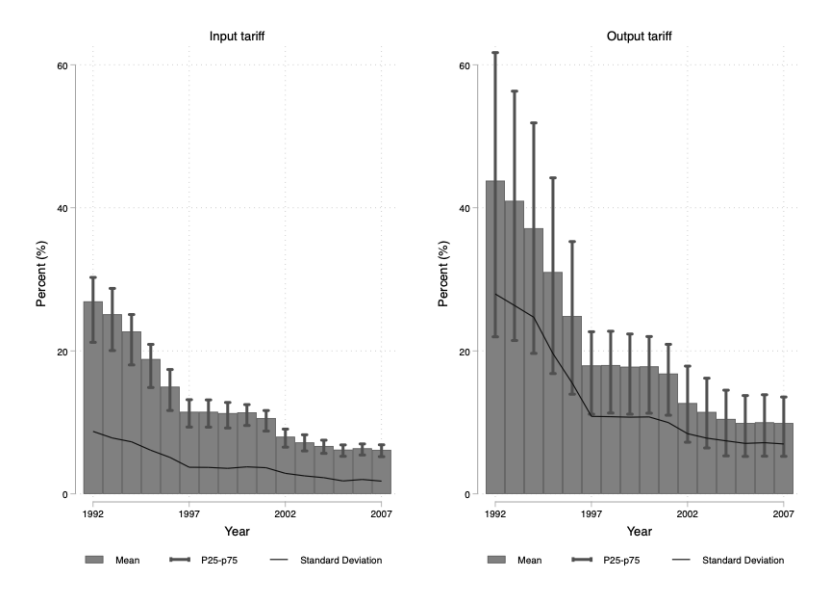

Figure 2: Evolution of Input and Output Tariffs, 1992-2007 (CIC-4)

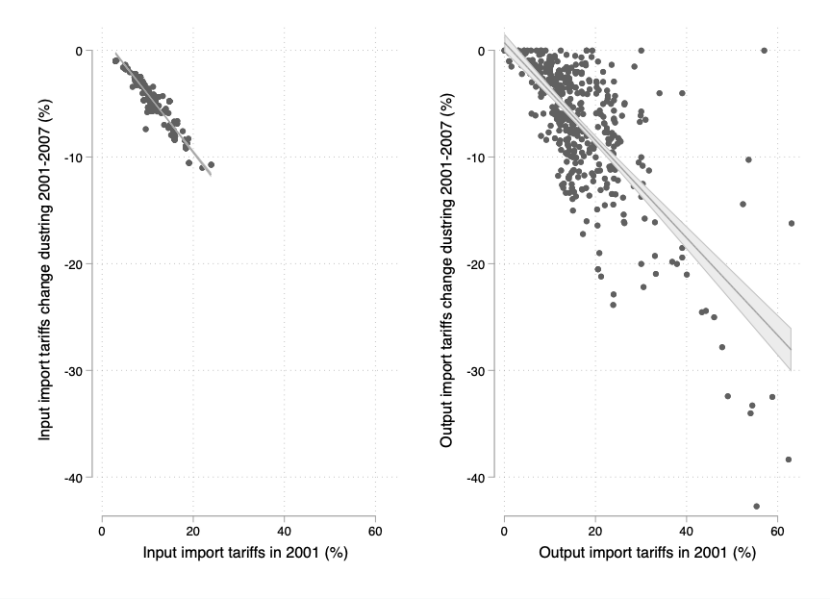

Figure 3: Correlation between Tariffs in 2001 and Changes in Tariffs over 2001-2007

In addition, when China entered the WTO, there was large industry heterogeneity in import tariffs. The reduction in tariffs after China's accession to the WTO also showed great heterogeneity. Figure 3 shows the relationship between the level of input and output tariffs in 2001 and the corresponding changes in tariffs from 2001 to 2007. Clearly, an industry's initial tariff level at the time of WTO entry was significantly positively correlated with its following tariff reduction. This phenomenon holds for both input and output tariffs. This study uses this feature in a DID empirical method to explore the impact of trade liberalization.

4.2.2 WTO Accession and the Labor Market

China's accession to the WTO constitutes a relevant and informative case study for several reasons. First, the accession to the WTO and the corresponding policy and institutional changes were nationwide and predetermined, and thus exogeneous to individual firms. Together with the stylized facts of tariff reduction depicted in Figures 2 and 3, WTO accession serves as a natural experiment for the DID setup. Second, due to the rich heterogeneity in industry compositions of import products and the varying tariff reductions across products, we can exploit this industrial variation to identify the impact of trade liberalization on firms' heterogeneity in monopsony power within industries. Third, during the period of China's WTO accession, the labor protection in China was weak and underdeveloped. Combined with regional labor mobility restrictions imposed by the "hukou" system, firms had significant monopsony power over their employees.

China's accession to the WTO has had far-reaching impacts on the Chinese labor market, and it has been the subject of lot of attention in the literature. Researchers have studied the effects of China's WTO accession on labor market outcomes in terms of employment (Han et al., 2022; Rodriguez-Lopez & Yu, 2024), wages (Dai et al., 2020; Han et al., 2012), education (Lin & Long, 2020), migration and migration institutions (Facchini et al., 2019; Tian, 2024), workers' health, (Fan et al., 2020) and career choice (Xu, 2020). The impacts on the labor market has not been uniform. Instead, they have exhibited various distributional effects in terms of initial labor market conditions (Dai et al., 2020), skill level (Fan et al., 2020; Fan, 2019; Han et al., 2012), and gender (Wang et al., 2020). With growing interest in imperfect competition in the labor market, there is mounting empirical evidence of the impact of WTO accession's impact on firms' monopsony power (Kondo et al., 2023; MacKenzie, 2021; Pham, 2023). However, the effect of trade liberalization on the heterogeneity of firms' monopsony power has been unexplored. Our paper aims to fill this gap.

4.3 Measurement of Key Variables

4.3.1 Markdowns

Firms' monopsony power is measured using markdowns, which are the ratio of the MRPL to wages. Our methods for estimating markdowns follows the work of Yeh et al. (2022) and Brooks et al. (2021).[21] By constructing a structural model with monopolistic competition in the product market and monopsonistic competition in the input market, the key point of their paper can be summarized as follows:

$$\mu_m^{\text{DLW}} = \mu \times \psi_m \tag{18}$$

where μ_m^{DLW} is the markup formula from De Loecker & Warzynski (2012) (DLW). The subscript m denotes different inputs, such as capital (K), labor (L) and the intermediate input (M). The variable μ represents the firm's markup in the product market. The variable ψ_m represents the firms markdown in the input market m. Equation (18) shows that when the input market is not perfectly competitive, the DLW formula markup is the product of the true markup and the input-specific markdown. Since μ does not vary with the inputs, we can take the ratio of equation (18) for different inputs to eliminate μ, that is:

$$\frac{\mu_m^{\text{DLW}}}{\mu_{m'}^{\text{DLW}}} = \frac{\psi_m}{\psi_{m'}} \tag{19}$$

Yeh et al. (2022) further assume that there exists a factor (empirically, we use the intermediate input) for which all firms are price takers,[22] that is, $\psi_M \equiv 1$. With this assumption and focusing on the labor market, equation (19) can be further expressed as follows:

$$\frac{\mu_L^{\text{DLW}}}{\mu_M^{\text{DLW}}} = \frac{\psi_L \times \mu}{\psi_M \times \mu} = \psi_L$$

Equation (19) is at the core of our methodology for estimating the markdown. It shows that the labor markdown can be obtained by dividing the two DLW markups. We estimate the DLW formula markup according to DLW, which is:

$$\mu_m^{\text{DLW}} = \frac{\theta_m}{\alpha_m} \tag{20}$$

where θ_m refers to the output elasticity of input m, which can be obtained by production function estimation, and α_m denotes the firm-specific expenditure share of input m, which is directly observable in the data.[23] We adopt the control function approach to estimate the gross production function. We use Ackerberg

[21] Caselli et al. (2021) and Morlacco (2019) apply a similar algorithm. Moreover, our model is consistent with Yeh et al. (2022), and their algorithm can be directly applied to our estimation.

[22] Appendix E provides a detailed discussion to validate the assumption of using intermediate input as the flexible input.

[23] Since we can not observe quantity in the ASIF database, we adjust the factor share by using the exponential of the first-stage regression residual from the production function estimation, according to DLW.

et al. (2015) (ACF) method as the baseline for the empirical analysis since it has been widely accepted in influential research. Moreover, Gandhi et al. (2020) (GNR) point out that the estimations of the gross output production function and the value-added production function are not interchangeable theoretically. The former method may confront a lack of identification when estimating the output elasticity of intermediate input. Nevertheless, Gandhi et al. (2020) identify the output elasticity of the intermediate input by using the cross-equation constraint between the production function and the first-order condition with respect to the intermediate input. This allows the output elasticity of the input to differ across firms within the same industry. Therefore, we draw from Gandhi et al. (2020) and DLW to estimate the markdown for a robustness check. We also use other production function estimation methods (Levinsohn & Petrin, 2003) (LP) to estimate the markup and markdown as additional robustness checks since they differ from each other in the timing assumption of labor determination.[24]

4.3.2 Input and Output Tariffs

The output tariff is obtained by aggregating the Harmonized System (HS) 8-digit-level product tariff by using the correspondence table between the CIC code and the HS code, which is the following:

$$\text{OutputTariff}_{st} = (\sum_{p \in s} \tau_{pt})/n_{st} \tag{21}$$

where s and p denote industry (CIC-4) and product (HS-8), respectively; t denotes year; τ denotes product tariff; and n_s refers to the total number of products in industry s. The aggregation is an unweighted average, to avoid bias caused by the negative correlation between the trade volume and tariff (Amiti & Konings, 2007; Brandt et al., 2017). Then, following Amiti & Konings (2007), input tariffs are a weighted average of output tariffs, with the weights given by the input share from the 2002 Chinese Input-Output Table.

$$\text{InputTariff}_{st} = \sum_{s'} w_{s's}^{2002} \times \text{OutputTariff}_{s't}, \text{where } w_{s's}^{2002} = \frac{\text{input}_{s's}^{2002}}{\sum_{s''} \text{input}_{s''s}^{2002}} \tag{22}$$

4.4 Level of Labor Market Power in China

Table 3 presents the summary statistics for the important variables used in our data analysis. The average value of the markdown is 1.52, which means that workers only capture 65.8% of their contribution to the revenue.[25] The median value of the estimated markdown is 0.94, indicating that the distribution of the markdown is skewed to the right, which is also in concert with Pham (2023)'s finding for China and Kusaka

[24] Appendix B displays the relevant summary statistics and figures for the markdown and the estimated average output elasticity of different production factors for different industries .

[25] Yeh et al. (2022) estimate the markdown for the US manufacturing industry and find a value of 1.53, which implies that workers only earn 65.4% of their contribution. Other work includes Kusaka (2023) on Columbia (1.175, 85.1%), Amodio & Roux (2022) on Colombia (1.4, 71.4%), Pham (2023) on China (2.14, 46.7%), and Hoang et al. (2022) on Vietnam (2.2, 45.0%).

(2023)'s finding for Colombia. Table 3 also reveals that intermediate input accounts for a large proportion of firms' input, which makes it a more suitable option to serve as a flexible input since there is less measurement error.

Table 3: Summary Statistics

	Mean	Median	SD
Markup	1.12	1.1	0.17
Markdown	1.52	0.9	1.85
Gross Output (Real Value, million RMB)	46.04	17.67	86.74
Value Added (Real Value, million RMB)	14.21	5.05	28.88
Intermediate Input (Real Value, million RMB)	32.66	12.62	58.98
Capital (Real Value, million RMB)	15.64	4.42	33.8
Employment	216.62	110	307.84
Number of the Observations		1,913,440	

Note: The sample is winsorized at 3 percent on both sides of the variables, by CIC-2-digit industry and year.

Figure 4 displays the evolution of the average markdown over our sample period. There is an overall upward-sloping trend of markdown, which implies that employers have incremental labor market power over workers. This is in line with the downward-sloping labor income share and upward-sloping average working hours as shown in Appendix B, Figure B1.

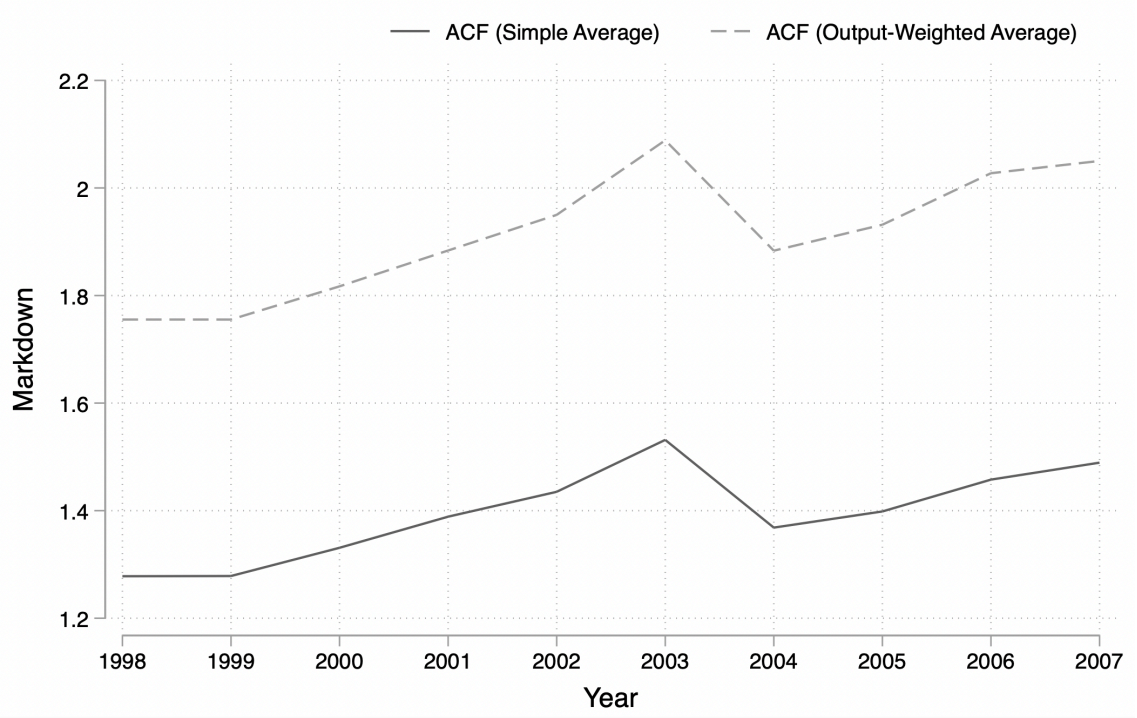

Figure 4: Evolution of the Average Markdown, 1998-2007

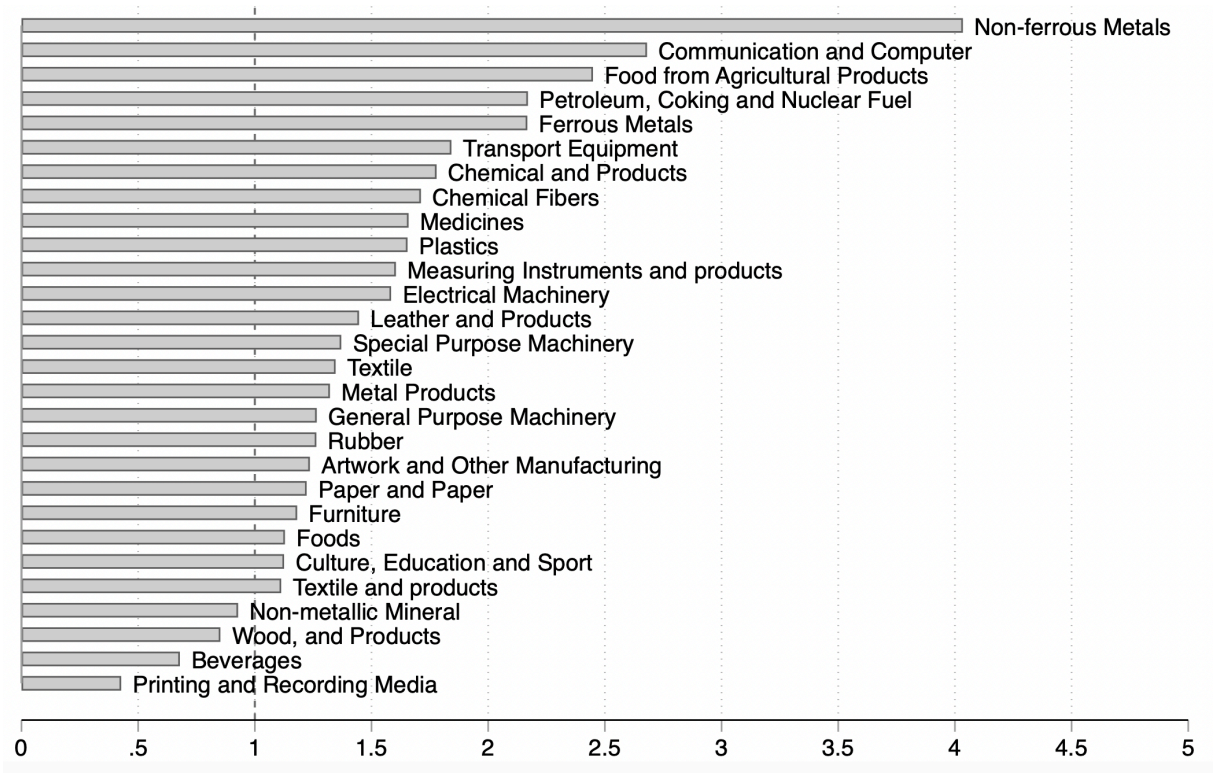

Figure 5: Estimated Markdowns for CIC-2 Industries

Figure 5 presents the mean markdowns at the CIC-2 industry level. The average markdowns range from 0.42 to 4.03, with a mean value of 1.54. There is significant heterogeneity in average markdowns across CIC-2 industries. The industries with the highest markdowns are non-ferrous metals, communications and computers, and food from agricultural products. Conversely, the industries with the lowest markdowns are printing and recording media, beverages, and wood products. Appendix B, Figure B3 shows the correlation pattern between labor market power and several observed CIC-2 industry-level attributes. Firms in capital-intensive, male worker-intensive, and skilled labor-intensive industries tend to have greater labor market power over their workers. This observation is broadly consistent with recent findings in the literature. For instance, Rubens et al. (2024) demonstrate that firms in the non-ferrous metals and mining industries wield significant bargaining power due to the concentration of young, male, and migrant workers. Similarly, Pham (2023) highlights that firms in female-intensive industries, such as textiles, leather, and printing and recording media, exhibit lower labor market power. Conversely, firms in skilled labor-intensive industries, such as communications and computers, pharmaceuticals, and measuring instruments, have higher labor market power. Furthermore, the lower left panel of Figure B3 shows that industry-level labor market power decreases with increased union coverage, which may explain the lower labor market power in the beverage, printing, and recording media industries.

5 Impact of Trade Liberalization on Labor Market Power

5.1 Level Effect

To maintain consistency and comparability, we investigate the impact of trade liberalization on firms' markdowns following Kondo et al. (2023) and Pham (2023):

$$\ln(\psi_{it}) = \alpha_0 + \alpha_1 \text{InputTariff}_{st} + \alpha_2 \text{OutputTariff}_{st} + \mathcal{X}'_{it}\eta + \lambda_i + \lambda_{ct} + \epsilon_{it} \tag{23}$$

where i, t and c denote firm, year, and city, respectively. The vector of controls, $\mathcal{X}_{it}$, includes the log of total output, the capital-labor ratio, the average wage, and one-period lagged log markups; λ_i denotes firm fixed effects; and λ_{ct} denotes city-year fixed effects.[26] Standard errors are clustered at the CIC-2 industry level. Consistent with the findings of Kondo et al. (2023) and Pham (2023), Table 4 shows that input trade liberalization reduces firms' labor market power while output trade liberalization has no significant effect.

Table 4: Effect of Trade Liberalization on the Markdown

Dependent Variables ln(Markdown)	(1)	(2)	(3)	(4)
Input Tariff	2.070***	2.418***		
	(0.632)	(0.667)		
Output Tariff		-0.211		
		(0.133)		
Input Tariff$_{t-1}$			2.219***	2.498***
			(0.611)	(0.673)
Output Tariff$_{t-1}$				-0.171
				(0.129)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
Observations	1,286,840	1,286,840	1,286,840	1,286,840
Adjusted R^2	0.885	0.885	0.885	0.885

Note: Robust standard errors clustered at the CIC-2 level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. The control variables include the total output, the capital-labor ratio, the average wage and one-period lagged markups. These variables all enter the regression in natural logs.

Motivated by our model and Pham (2023), we next investigate the heterogeneous impact of input trade liberalization from the perspective of firms' initial intermediate input intensity following equation (24):

$$\ln(\psi_{it}) = \alpha_0 + (\alpha_1 \text{InputTariff}_{st} + \alpha_2 \text{OutputTariff}_{st}) \times \ln(\text{M/L})_{t0} + \mathcal{X}'_{it}\eta + \mathcal{X}'_{st}\gamma + \lambda_i + \lambda_{ct} + \epsilon_{it} \tag{24}$$

[26] City-year fixed effects help to control the effect of the labor market development. For instance, the minimum wage standards are established through negotiations among provincial, city, and county governments, with most variations occurring at the city level (Mayneris et al., 2018). Similarly, reforms in labor mobility restrictions also take place at the city level (Brzezinska, 2021).

where the vector of controls, $\mathcal{X}_{it}$, remains the same and the vector of controls $\mathcal{X}_{st}$ at the CIC-4 level includes input and output tariffs. Table 5 presents the results. The positive coefficients of the interaction terms between input tariff and firms' initial intermediate input-labor ratio suggest that the impact of input trade liberalization on reducing firms' labor market power is more significant for intermediate-input intensive firms.

Table 5: Adjustment Effect of Firms' Initial Intermediate Input-Labor Ratio

Dependent Variables ln(Markdown)	(1)	(2)	(3)	(4)
Input Tariff $\times$ ln(M/L)$_{t0}$	2.069***	2.127***		
	(0.289)	(0.398)		
Output Tariff $\times$ ln(M/L)$_{t0}$		-0.027		
		(0.079)		
Input Tariff$_{t-1}\times$ ln(M/L)$_{t0}$			1.959***	1.984***
			(0.274)	(0.358)
Output Tariff$_{t-1}\times$ ln(M/L)$_{t0}$				-0.008
				(0.060)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
Observations	1,285,306	1,285,306	1,285,306	1,285,306
Adjusted R^2	0.887	0.887	0.887	0.887

Note: Robust standard errors clustered at the CIC-2 level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. The firm-level control variables include the total output, capital-labor ratio, average wage, and one-period lagged markups. These variables all enter the regression in natural logs. The CIC-4-level controls variables include input and output tariffs.

As pointed out by Macedoni & Tyazhelnikov (2024), firms' markup over the unit costs of production (i.e., overall market power) is composed of both the markups in the product market and the markdown in the input market. When trade liberalization decreases the market power in one market, it will increase the market power in the other market. Trottner (2023) also emphasizes the interplay between markups and markdowns. He suggests that monopsony might magnify or entirely undo any pro-competitive effects of market integration on markdowns and markups. Motivated by these theoretical considerations, we further analyze the impact of trade liberalization on firms' markups and overall market power (i.e., both markup and markdown).

Table 6: Effect of Trade Liberalization on Markups and Combined Market Power

Dependent Variables				Panel A
ln(Markup)	(1)	(2)	(3)	(4)
Input Tariff	-0.505**	-0.440**		
	(0.228)	(0.204)		
Output Tariff		-0.040		
		(0.044)		
Input Tariff$_{t-1}$			-0.426*	-0.399*
			(0.237)	(0.216)
Output Tariff$_{t-1}$				-0.017
				(0.036)
Observations	1,786,211	1,786,211	1,654,800	1,654,800
Adjusted R^2	0.390	0.390	0.393	0.393
Dependent Variables				Panel B
ln(Market Power)	(1)	(2)	(3)	(4)
Input Tariff	1.538**	1.960***		
	(0.674)	(0.667)		
Output Tariff		-0.257**		
		(0.123)		
Input Tariff$_{t-1}$			1.740**	2.060***
			(0.695)	(0.716)
Output Tariff$_{t-1}$				-0.199
				(0.128)
Observations	1,786,211	1,786,211	1,654,800	1,654,800
Adjusted R^2	0.845	0.845	0.849	0.849
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at the CIC-2 level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. The control variables include the total output, capital-labor ratio, and average wage. These variables all enter the regression in natural logs.

Table 6 presents the result. Consistent with Brandt et al. (2017) and Fan et al. (2018), panel A shows that input trade liberalization increases firms' product market power, while output trade liberalization has no significant effect. Overall, panel B shows that input trade liberalization reduces firms' aggregate market power, which suggests that the "pro-competitive" effect of input trade liberalization on the labor market outweighs the "anti-competitive" effect of input trade liberalization on the product market.

5.2 Distribution Effect

As Figure 3 indicates, the initial levels of input and output tariffs in 2001 are positively correlated with the magnitude of the tariff reduction over 2001-2007. As a result, we can use the DID method to explore

the impact of trade liberalization. The initial levels of the input and output tariffs act as group variables, and industries with a high initial tariff (treatment group) experience a larger extent of tariff reduction, while industries with a low initial tariff (control group) experience a smaller extent of tariff reduction. Guided by our model prediction in equation (17), the empirical specification is defined as follows:

$$\text{var}\log\psi_{st} = \beta_0 + (\beta_1 \text{InputTariff}_s^{2001} + \beta_2 \text{OutputTariff}_s^{2001}) \cdot \text{Post02}_t + \mathcal{X}'_{st}\gamma + \lambda_s + \lambda_t + \epsilon_{st} \tag{25}$$

where s and t denote industry (CIC-4) and year, respectively, and $\text{var}\log\psi_{st}$ refers to the variance of log markdown.[27] Moreover, $\text{InputTariff}_s^{2001}$ denotes the input tariff at the CIC-4 industry level in 2001, while $\text{OutputTariff}_s^{2001}$ denotes the output tariff at the CIC-4 industry level in 2001. Post02_t indicates the WTO accession dummy variable, and it takes the value of one in 2002 and thereafter, otherwise 0. λ_s is CIC-4 industry fixed effects. To ensure that our identification is not threatened by macro trends, we further control year fixed effects, λ_t. Standard errors are clustered at the CIC-4 industry level. To eliminate the potential threat of omitted variable bias, we also add control variables at the CIC-4 industry level, denoted by $\mathcal{X}'_{st}$, including the weighted average TFP, mean value of fixed assets and number of firms. The parameters of interest are β_1 and β_2. If $\beta_1(\beta_2)$ is positive, it indicates that the input tariff (output tariff) reduction increases the variance in log markdown within the industry, and vice versa.

5.2.1 Baseline Results

Table 7 reports the baseline results. In column (1), we only include the regressor of interest, industry, and year fixed effects. Column (1) indicates that the coefficient of $\text{InputTariff}_s^{2001} \cdot \text{Post02}_t$ is statistically significant and negative. Since the tariff level in 2001 is positively correlated with tariff reduction between 2001 and 2007, the higher the tariff level is in 2001, the larger is the trade liberalization that is realized. Hence, the results demonstrate that input tariff reduction reduces the variance in log markdown. In contrast, the coefficient of $\text{OutputTariff}_s^{2001} \cdot \text{Post02}_t$ is negative but statistically insignificant, which means that the reduction in the output tariff has no impact.

In column (2), we take time-varying, industry-level attributes into account. Following Lu & Yu (2015), we control the mean value of fixed assets and the number of firms in each industry to account for the entry barrier. The results are robust to these additional controls. The DID specification requires that the tariff in 2001 be randomly determined. However, this may not be the truth. Following Lu & Yu (2015), we identify variables that had a significant impact on the tariff in 2001. As shown in Appendix B Tables B.5 and B.6, four determinants stand out: (1) the output share of SOEs, (2) the output share of domestic firms, (3) export intensity, and (4) the average wage per worker. Taking the interaction terms between the tariff

[27] There are some negative values for markdowns. If we simply take the log of the markdown per se, the negative values are dropped, which significantly changes the distribution (and hence the variance) of the markdowns within the manufacturing industry. In light of this, we adopt a hyperbolic sine transformation, which is: $\text{var}\log\psi_s \triangleq \text{var}\log(\psi_{sj} + \sqrt{{\psi_{sj}}^2 + 1})$.

determinants and Post02$_t$ into account, we show in column (3) that our results still remain.

Table 7: Baseline Results

Dependent variables: Variance in ln(markdown)	(1)	(2)	(3)
Input Tariff$_{01}$ × Post$_{02}$	-0.485***	-0.493***	-0.462***
	(0.153)	(0.152)	(0.140)
Output Tariff$_{01}$ × Post$_{02}$	-0.059	-0.057	-0.039
	(0.055)	(0.054)	(0.045)
ln(Weigthed TFP)	0.025***	0.026***	0.022***
	(0.007)	(0.006)	(0.006)
ln(TFP_s)	-0.058	-0.048	-0.082**
	(0.046)	(0.045)	(0.042)
Average fixed assets (ln)		-0.016	-0.015
		(0.015)	(0.016)
Number of firms (ln)		-0.010	-0.002
		(0.010)	(0.011)
Output share of SOEs$_{01}$ × Post$_{02}$			0.095***
			(0.028)
Output share of domestic$_{01}$ × Post$_{02}$			0.023
			(0.040)
Average wage per worker$_{01}$			-0.064***
			(0.019)
Export Intensity$_{01}$ × Post$_{02}$			-0.084***
			(0.020)
Year FE	Yes	Yes	Yes
CIC-4 FE	Yes	Yes	Yes
Observations	4,040	4,040	4,001
Adjusted R^2	0.775	0.776	0.799

Note: Robust standard errors clustered at the CIC-4 level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels.

5.2.2 Robustness Check

Identifying Assumption. Bajona & Chu (2010) point out that China's WTO accession protocol not only imposed requirements on trade policy, but also proposed the requirement that the Chinese government had to reduce its subsidies to the state-owned sectors. Meanwhile, alongside the WTO accession, China also experienced SOE reform, relaxation of foreign direct investment, and export expansion (Bai et al., 2006; Li, 2018; Lu et al., 2019). To control for these contemporaneous policy reforms, we take three CIC-4 industry-level controls into account: the share of SOEs among domestic firms, number of foreign-invested firms and total exports. The results are reported in column (1) in Table 8. These additional controls leave the main result unaffected.

In addition, as a placebo test, we investigate the impact of trade liberalization on the variance of log

markdown in the pre-WTO period (i.e., 1998-2001), following Topalova (2010). As Figure 3 shows, the reduction of the import tariff during this period was subtle. Hence, it is expected that the coefficients of the regressor of interest would be insignificant. Column (2) in Table 8 verifies our prediction.

Collapsed DID. There may be concern that the traditional DID estimation may underestimate the standard error. Following Bertrand et al. (2004), we collapse the panel data into a "pre" and "post" periods, i.e., one before and one after the WTO accession. The results are shown in Table 8 in column (3), and they are also in line with our baseline results.

Table 8: Checks on Identifying Assumptions and Collapsed DID

Dependent variables: Variance in ln(markdown)	(1)	(2)	(3)
Input $\text{Tariff}_{01} \times \text{Post}_{02}$	-0.458***		-0.458***
	(0.123)		(0.127)
Output $\text{Tariff}_{01} \times \text{Post}_{02}$	-0.042		-0.056
	(0.040)		(0.044)
SOE share	-0.069***	0.008	
	(0.026)	(0.049)	
FDI (ln)	-0.008	0.010	
	(0.005)	(0.007)	
Total exports (ln)	0.002	0.003	
	(0.003)	(0.005)	
Input Tariff		0.213	
		(0.233)	
Output Tariff		-0.140	
		(0.103)	
Year FE	Yes	Yes	Yes
CIC-4 FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
Tariff determinants and Post	Yes	Yes	Yes
Observations	3,771	1,507	790
Adjusted R^2	0.848	0.898	0.877

Note: Robust standard errors clustered at the CIC-4 level are in parentheses. ***, **, * denote significance at 1%, 5%, 10% levels. Each column includes control variables, and the interaction terms between Post02_t and tariff determinant.

Variance Calculation Cutoff. Since the variable of interest is the variance of the log value of markdown and there is huge industry-level heterogeneity in terms of both the tariff reduction and the number and composition of firms, there may be concern that the lack of a sufficient number of firms may distort the calculation of variance. In response to this concern, we set different cutoff values for the minimum number of firms needed when we calculate the variance. The industry-year cell with the number of firms less than the cutoff is dropped from the sample. Table 9 presents the results, and the columns correspond to different thresholds. The results show that input tariff reduction is associated with a decrease in the markdown

heterogeneity, while output tariff reduction has no significant impact. Thus, our results are not affected by the variance calculation.

Table 9: Variance Calculation Cutoff

Dependent variables: Variance in ln(markdown)	(1)	(2)	(3)
Input $\text{Tariff}_{01} \times \text{Post}_{02}$	-0.432***	-0.384***	-0.290**
	(0.119)	(0.124)	(0.130)
Output $\text{Tariff}_{01} \times \text{Post}_{02}$	-0.025	-0.019	-0.023
	(0.038)	(0.044)	(0.044)
Year FE	Yes	Yes	Yes
CIC-4 FE	Yes	Yes	Yes
Observations	3,416	2,926	2,187
Adjusted R^2	0.879	0.891	0.901
Cutoff	50	100	200

Note: Robust standard errors clustered at the CIC-4 level are in parentheses. ***, **, * denote significance at 1%, 5%, 10% levels. Each column includes control variables, and the interaction terms between Post02_t and tariff determinant, and total exports, the share of SOE firms and the number of foreign-invested firms.

Parallel Trends Assumption. A prerequisite for using the DID estimation strategy is that the treatment and control groups should satisfy the parallel trends assumption before the policy shock. We use the event study approach to check whether this assumption is satisfied:

$$\begin{aligned} \text{var}\log\psi_{st} =& \beta_0 + \sum_{m=1998}^{m=2007} \beta_m \text{InputTariff}_s^{2001} \cdot \text{m}_t + \sum_{n=1998}^{n=2007} \beta_n \text{OutputTariff}_s^{2001} \cdot \text{n}_t \\ &+ \mathcal{X}'_{st}\gamma + \lambda_s + \lambda_t + \epsilon_{st} \end{aligned} \tag{26}$$

where we set the last year before China's accession to the WTO (i.e., 2001) as the base year; m_t and n_t are year dummy variables; and other things are held equal.

Figure 6 exhibits the estimates of β_m and β_n and the 95% confidence intervals. The estimates of β_m and β_n are insignificant between 1998 and 2001, which suggests that there was no ex-ante difference between the treatment and control groups. Moreover, the impact of input trade liberalization on the variance of log markdown is negative, and the magnitude is increasing, while output trade liberalization has no significant effect.

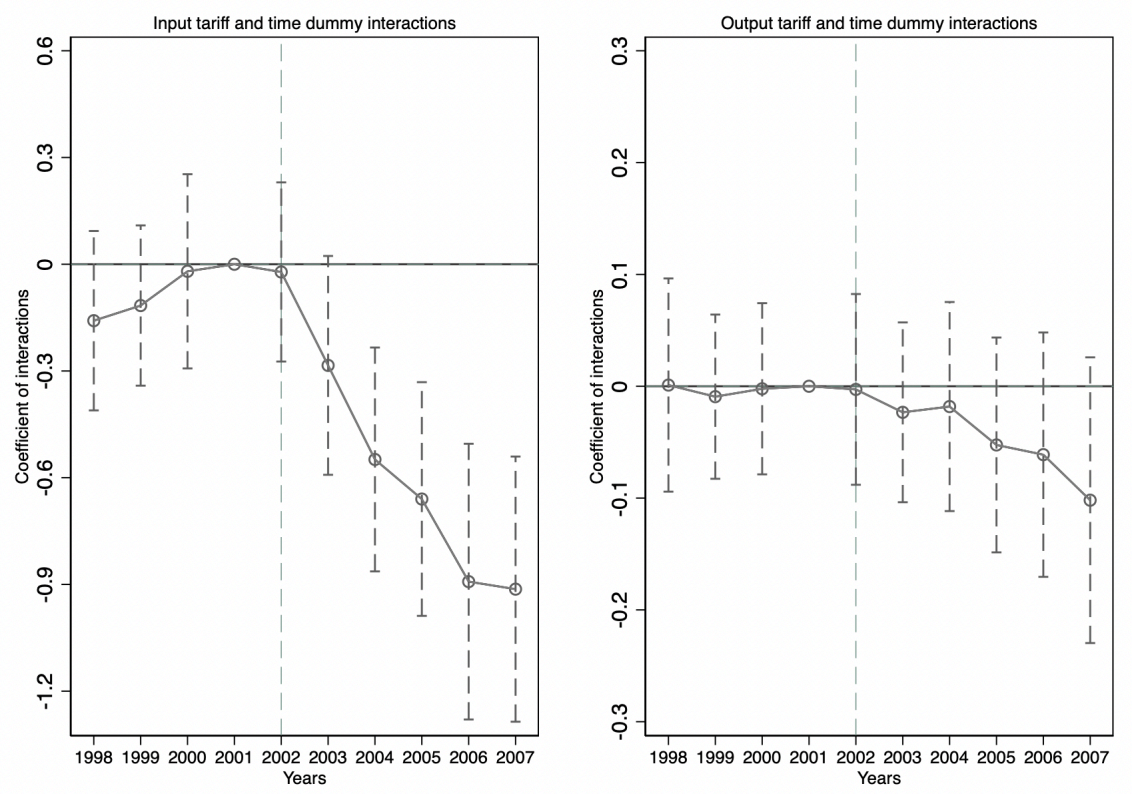

Figure 6: Dynamic Effects of Trade Liberalization

Alternative Measure of Markdowns. As shown in section 4, the markdown is obtained from production function estimation. To capture the heterogeneity of firms' monopsony power, we further use two alternative production function estimation methods. First, we follow the nonparametric method of estimating the gross output production function proposed by Gandhi et al. (2020). This method performs better in identifying the output elasticity of intermediate input and allows output elasticities to vary across firms even within the same sector. Second, we estimate the translog production function, which also allows varying output elasticities within sectors as follows:

$$\begin{aligned}\tilde{q}_{it} = \beta_l \tilde{l}_{it} + \beta_k \tilde{k}_{it} + \beta_m \tilde{m}_{it} + \beta_{ll} \tilde{l}_{it}^2 + \beta_{kk} \tilde{k}_{it}^2 + \beta_{mm} \tilde{m}_{it}^2 + \\ \beta_{lk} \tilde{l}_{it} \tilde{k}_{it} + \beta_{lm} \tilde{l}_{it} \tilde{m}_{it} + \beta_{km} \tilde{k}_{it} \tilde{m}_{it} + \beta_{lkm} \tilde{l}_{it} \tilde{k}_{it} \tilde{m}_{it} + \omega_{it} + \varepsilon_{it}\end{aligned} \tag{27}$$

where the variables with a tilde refer to the log value. For instance, $\tilde{q}_{it}$ denotes the log of the output of the firm. The variable ω_{it} indicates firm-specific productivity, and ε_{it} is an independent and identically distributed error. Similarly, we estimate the translog production function for each CIC-2 industry separately. The regression results are displayed in Table 10. All the coefficients show patterns that are consistent with the baseline analysis.

Table 10: Alternative Measure of the Markdown

Dependent variables:	LP(Translog)	ACF(Translog)	GNR
Variance in ln(markdown)	(1)	(2)	(3)
Input $\text{Tariff}_{01} \times \text{Post}_{02}$	-2.666***	-1.387**	-0.351**
	(0.934)	(0.646)	(0.169)
Output $\text{Tariff}_{01} \times \text{Post}_{02}$	0.243	-0.216	0.003
	(0.265)	(0.145)	(0.053)
Year FE	Yes	Yes	Yes
CIC-4 FE	Yes	Yes	Yes
Observations	3,876	3,884	3,288
Adjusted R^2	0.848	0.868	0.776

Note: Robust standard errors clustered at the CIC-4 level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. Each column includes control variables, the interaction terms between Post02_t and tariff determinant, other contemporaneous policy reforms and total exports.

5.2.3 Quantile Regression

To analyze how trade liberalization affects the variance, we investigate the response of the log of the markdown at different quantiles of the value of log markdown. In particular, we regress p5, p25, p50, p75, p95, and the mean value of the log of the markdown on the aforementioned regressor. The results are summarized in Table 11.

Input trade liberalization reduces firms' monopsony power, and this *"pro-competitive"* effect can be found in low quantiles and high quantiles. However, the effect is stronger in high quantiles than low quantiles, which shifts the distribution to the left and makes the right tail shorter. As a result, the distribution of the log of the markdown flattens and the variance in log markdown decreases.

Table 11: Quantile Regression

Dependent variables:	(1)	(2)	(3)	(4)	(5)	(6)
Quantile of ln(markdown)	Mean	p5	p25	p50	p75	p95
Input $\text{Tariff}_{01} \times \text{Post}_{02}$	-0.425**	-0.105	-0.344***	-0.400**	-0.402	-1.147***
	(0.170)	(0.071)	(0.129)	(0.179)	(0.266)	(0.368)
Output $\text{Tariff}_{01} \times \text{Post}_{02}$	-0.080	0.018	0.009	-0.093	-0.198**	-0.096
	(0.066)	(0.027)	(0.058)	(0.074)	(0.097)	(0.134)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
CIC-4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,771	3,771	3,771	3,771	3,771	3,771
Adjusted R^2	0.917	0.751	0.888	0.911	0.892	0.812

Note: Robust standard errors clustered at the CIC-4 level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. Each column includes control variables, the interaction terms between Post02_t and tariff determinant, other contemporaneous policy reforms and total exports.

5.2.4 Heterogeneity Analysis

In this section, we investigate the heterogeneous impact of trade liberalization on the markdown distribution. First, we divide the firms into incumbents and exits/entrants. Melitz (2003) emphasizes that these firms differ in productivity. Moreover, the incumbent firms may have greater market power and respond differently to changes in trade costs compared with the exits/entrants (Arkolakis et al., 2019). The first two columns in Table 12 exhibit the results. The effect of tariff reduction is remarkably large for incumbent firms. Second, we divide the firms into SOEs and non-SOEs. SOEs do not aim for profit maximization; instead, they undertake the responsibility of stabilizing employment (Bai et al., 2006), and their autonomy in determining employment and wages is limited. The SOEs have priority over access to capital, land, and other production factors (Chen et al., 2019), which might reduce their incentive to increase profits by controlling wages and employment. Columns (3) and (4) in Table 12 show the results for SOEs and non-SOEs, respectively, and the effect of input trade liberalization is larger for non-SOEs. Manning (2003b) proposes that the labor supply elasticity faced by individual firms is an important determinant of firms' labor market power. The more elastic the labor supply is, the less is firms' labor market power. Hence, we split up the sample into two groups using data provided by Fan et al. (2011): firms located in provinces with high labor mobility and those in provinces with low labor mobility. The influence of input trade liberalization is significantly larger in provinces with low labor mobility.

Overall, the effect of trade liberalization on the markdown distribution is noteworthy, particularly for incumbent firms, non-SOEs, provinces with limited labor mobility, and inland provinces where firms tend to have more monopsony power. These findings are consistent with the findings of Lu & Yu (2015), which show that the impact of trade liberalization is greater when product markets are more monopolized.

Table 12: Heterogeneity Analysis

Dependent variables:	(1)	(2)	(3)	(4)	(5)	(6)
Variance in ln(markdown)	Incumbent	Exit/Entrant	SOEs	Non-SOEs	High Mobility	Low Mobility
Input $\text{Tariff}_{01} \times \text{Post}_{02}$	-0.579***	-0.453***	-0.372*	-0.502***	-0.394***	-0.686***
	(0.185)	(0.165)	(0.223)	(0.142)	(0.148)	(0.166)
Output $\text{Tariff}_{01} \times \text{Post}_{02}$	0.078	-0.004	-0.094	-0.034	(-0.047)	(0.044)
	(0.052)	(0.051)	(0.071)	(0.041)	(0.042)	(0.052)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
CIC-4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,761	3,764	3,749	3,770	3,769	3,765
Adjusted R^2	0.657	0.639	0.569	0.807	0.727	0.705

Note: Robust standard errors clustered at the CIC-4 level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. Each column includes control variables, the interaction terms between Post02_t and tariff determinant, other contemporaneous policy reforms and total exports.

6 Conclusion

This paper studies the impact of trade liberalization on heterogeneity of the labor market power of manufacturing firms in China, which, as our model shows, is a potential source of misallocation in our model. The model incorporates monopolistic competition in the product market and monopsonistic competition in the labor market. The findings show that heterogeneous preferences of workers for different occupations and the distinct occupation compositions of firms serve as new sources of heterogeneous monopsony power across firms. From the micro point of view, firms with monopsony power produce less, use less input, charge higher prices, and use more non-labor input. From the macro point of view, heterogeneous monopsony power across firms gives rise to misallocation and results in efficiency loss. The variance in log markdown serves as a sufficient statistic of the negative impact of heterogeneous monopsony power across firms on total production efficiency. Furthermore, our model shows that input trade liberalization is associated with reduced markdown heterogeneity and output trade liberalization has the opposite effect.

Using China's accession to the WTO as a semi-natural experiment, we investigated the impact of trade liberalization on the labor market power and labor market power heterogeneity of manufacturing firms, with detailed data on firms' production and tariffs. The empirical results support that input trade liberalization decreases the variance in log markdown and mitigates the misallocation of the factors of production across firms, while output trade liberalization has no significant effect. Overall, our work suggests that the reallocation effect of trade in an imperfectly competitive labor market serves as an important channel for gains from trade.

References

Ackerberg, Daniel A, Kevin Caves & Garth Frazer. 2015. Identification properties of recent production function estimators. *Econometrica* 83(6). 2411–2451.

Ahn, JaeBin, Amit K Khandelwal & Shang-Jin Wei. 2011. The role of intermediaries in facilitating trade. *Journal of International Economics* 84(1). 73–85.

Ahsan, Reshad N & Devashish Mitra. 2014. Trade liberalization and labor's slice of the pie: Evidence from indian firms. *Journal of Development Economics* 108. 1–16.

Amiti, Mary & Jozef Konings. 2007. Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *American Economic Review* 97(5). 1611–1638.

Amodio, Francesco & Nicolás de Roux. 2022. Measuring labor market power in developing countries: Evidence from colombian plants .

Arkolakis, Costas, Arnaud Costinot, Dave Donaldson & Andrés Rodríguez-Clare. 2019. The elusive pro-competitive effects of trade. *The Review of Economic Studies* 86(1). 46–80.

Atkin, David & Amit K Khandelwal. 2020. How distortions alter the impacts of international trade in developing countries. *Annual Review of Economics* 12. 213–238.

Bai, Chong-En, Jiangyong Lu & Zhigang Tao. 2006. The multitask theory of state enterprise reform: Empirical evidence from china. *American Economic Review* 96(2). 353–357.

Bai, Peiwen & Wenli Cheng. 2016. Labour misallocation in china: 1980–2010. *Applied Economics* 48(25). 2321–2332.

Bai, Yan, Keyu Jin & Dan Lu. 2024. Misallocation under trade liberalization. *American Economic Review* 114(7). 1949–1985.

Bajona, Claustre & Tianshu Chu. 2010. Reforming state owned enterprises in china: Effects of wto accession. *Review of Economic Dynamics* 13(4). 800–823.

Bertrand, Marianne, Esther Duflo & Sendhil Mullainathan. 2004. How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics* 119(1). 249–275.

Boal, William M & Michael R Ransom. 1997. Monopsony in the labor market. *Journal of Economic Literature* 35(1). 86–112.

Booth, Alison L, Gylfi Zoega et al. 2000. *Why do firms invest in general training?:'good'firms and'bad'firms as a source of monopsony power*, vol. 2536. Centre for Economic Policy Research.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang & Yifan Zhang. 2017. Wto accession and performance of chinese manufacturing firms. *American Economic Review* 107(9). 2784–2820.

Brandt, Loren, Johannes Van Biesebroeck & Yifan Zhang. 2012. Creative accounting or creative destruction? firm-level productivity growth in chinese manufacturing. *Journal of Development Economics* 97(2). 339–351.

Brandt, Loren, Johannes Van Biesebroeck & Yifan Zhang. 2014. Challenges of working with the chinese nbs firm-level data. *China Economic Review* 30. 339–352.

Brooks, Wyatt J, Joseph P Kaboski, Yao Amber Li & Wei Qian. 2021. Exploitation of labor? classical monopsony power and labor's share. *Journal of Development Economics* 150. 102627.

Brzezinska, Ida. 2021. The working dread? analysing the impact of the hukou reform on firms' monopsony power in china .

Burdett, Kenneth & Dale T Mortensen. 1998. Wage differentials, employer size, and unemployment. *International Economic Review* 257–273.

Cai, Hongbin & Qiao Liu. 2009. Competition and corporate tax avoidance: Evidence from chinese industrial firms. *The Economic Journal* 119(537). 764–795.

Card, David, Ana Rute Cardoso, Joerg Heining & Patrick Kline. 2018. Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics* 36(S1). S13–S70.

Card, David, Jörg Heining & Patrick Kline. 2013. Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics* 128(3). 967–1015.

Caselli, Mauro, Lionel Nesta & Stefano Schiavo. 2021. Imports and labour market imperfections: Firm-level evidence from france. *European Economic Review* 131. 103632.

Chen, Bo, Miaojie Yu & Zhihao Yu. 2017. Measured skill premia and input trade liberalization: evidence from chinese firms. *Journal of International Economics* 109. 31–42.

Chen, Cheng, Wei Tian & Miaojie Yu. 2019. Outward fdi and domestic input distortions: Evidence from chinese firms. *The Economic Journal* 129(624). 3025–3057.

Dai, Mi, Wei Huang & Yifan Zhang. 2020. Persistent effects of initial labor market conditions: The case of china's tariff liberalization after wto accession. *Journal of Economic Behavior & Organization* 178. 566–581.

Damoah, Kaku Attah. 2021. Markups, market imperfections, and trade openness: Evidence from ghana. *The World Bank Economic Review* 35(1). 92–116.

Dan, Sheng & Lu Yi. 2017. Does privatization of soes reduce worker's bargaining power? *Journal of Financial Research (In Chinese)* .

De Loecker, Jan, Catherine Fuss & Johannes Van Biesebroeck. 2018. Markup and price dynamics: linking micro to macro. Tech. rep. NBB Working Paper.

De Loecker, Jan, Pinelopi K Goldberg, Amit K Khandelwal & Nina Pavcnik. 2016. Prices, markups, and trade reform. *Econometrica* 84(2). 445–510.

De Loecker, Jan & Frederic Warzynski. 2012. Markups and firm-level export status. *American Economic Review* 102(6). 2437–2471.

Dobbelaere, Sabien & Quint Wiersma. 2020. The impact of trade liberalization on firms' product and labor market power. *IZA Discussion Paper No. 12951, Institute of Labor Economics, Bonn, Germany* .

Dorn, David, Lawrence F Katz, Christina Patterson, John Van Reenen et al. 2017. Concentrating on the fall of the labor share. *American Economic Review* 107(5). 180–85.

Edmond, Chris, Virgiliu Midrigan & Daniel Yi Xu. 2015. Competition, markups, and the gains from international trade. *American Economic Review* 105(10). 3183–3221.

Edmond, Chris, Virgiliu Midrigan & Daniel Yi Xu. 2023. How costly are markups? *Journal of Political Economy* 131(7). 1619–1675.

Egger, Hartmut, Udo Kreickemeier, Christoph Moser & Jens Wrona. 2021. Exporting and offshoring with monopsonistic competition. *The Economic Journal* 132(644). 1449–1488.

Epifani, Paolo & Gino Gancia. 2011. Trade, markup heterogeneity and misallocations. *Journal of International Economics* 83(1). 1–13.

Facchini, Giovanni, Maggie Y Liu, Anna Maria Mayda & Minghai Zhou. 2019. China's "great migration": The impact of the reduction in trade policy uncertainty. *Journal of International Economics* 120. 126–144.

Fajgelbaum, Pablo, Gene M Grossman & Elhanan Helpman. 2011. Income distribution, product quality, and international trade. *Journal of Political Economy* 119(4). 721–765.

Fan, Gang, Xiaolu Wang & Hengpeng Zhu. 2011. *China marketization index: Report on the relative progress of marketization in various regions in 2011*. Economic Science Press.

Fan, Haichao, Xiang Gao, Yao Amber Li & Tuan Anh Luong. 2018. Trade liberalization and markups: Micro evidence from china. *Journal of Comparative Economics* 46(1). 103–130.

Fan, Haichao, Faqin Lin & Shu Lin. 2020. The hidden cost of trade liberalization: Input tariff shocks and worker health in china. *Journal of International Economics* 126. 103349.

Fan, Jingting. 2019. Internal geography, labor mobility, and the distributional impacts of trade. *American Economic Journal: Macroeconomics* 11(3). 252–288.

Felix, Mayara. 2021. Trade, labor market concentration, and wages. *Job Market Paper* .

Foster, Lucia, John Haltiwanger & Chad Syverson. 2008. Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review* 98(1). 394–425.

Fox, Jeremy T. 2010. Estimating the employer switching costs and wage responses of forward-looking engineers. *Journal of Labor Economics* 28(2). 357–412.

Gandhi, Amit, Salvador Navarro & David A Rivers. 2020. On the identification of gross output production functions. *Journal of Political Economy* 128(8). 2973–3016.

Ge, Ying. 2014. Do chinese unions have "real" effects on employee compensation? *Contemporary Economic Policy* 32(1). 187–202.

Gould, Elise. 2014. Why america's workers need faster wage growth—and what we can do about it. *Economic Policy Institute Briefing Paper* 382.

Han, Jun, Runjuan Liu & Guofeng Wu. 2022. Trade policy uncertainty and employment evidence from chinese local labor markets. *Available at SSRN 4176041* .

Han, Jun, Runjuan Liu & Junsen Zhang. 2012. Globalization and wage inequality: Evidence from urban china. *Journal of international Economics* 87(2). 288–297.

Hoang, Trang, Devashish Mitra & Hoang Pham. 2022. Export market expansion, labor-market power, and labor shares: Evidence from a small open economy .

Hsieh, Chang-Tai & Peter J Klenow. 2009. Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics* 124(4). 1403–1448.

Hsu, Wen-Tai, Yi Lu & Guiying Laura Wu. 2020. Competition, markups, and gains from trade: A quantitative analysis of china between 1995 and 2004. *Journal of International Economics* 122. 103266.

Jha, Priyaranjan & Antonio Rodriguez-Lopez. 2021. Monopsonistic labor markets and international trade. *European Economic Review* 140. 103939.

Karabarbounis, Loukas & Brent Neiman. 2014. The global decline of the labor share. *The Quarterly Journal of Economics* 129(1). 61–103.

Kondo, Illenin, Yao Amber Li & Wei Qian. 2023. Trade liberalization and labor monopsony: Evidence from chinese firms. *Available at SSRN 4088005* .

Kusaka, Shoki. 2023. Markdowns and trade liberalization in developing countries: Evidence from colombia, 1977-2020. *SSRN Working Paper, No. 4466666* .

Lee, Chang Hee et al. 2009. *Industrial relations and collective bargaining in china*. ILO Geneva.

Lee, Eunhee. 2020. Trade, inequality, and the endogenous sorting ofheterogeneous workers. *Journal of International Economics* 125. 103310.

Levinsohn, James. 1993. Testing the imports-as-market-discipline hypothesis. *Journal of international Economics* 35(1-2). 1–22.

Levinsohn, James & Amil Petrin. 2003. Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies* 70(2). 317–341.

Li, Bingjing. 2018. Export expansion, skill acquisition and industry specialization: Evidence from china. *Journal of International Economics* 114. 346–361.

Lin, Faqin & Cheryl X Long. 2020. The impact of globalization on youth education: Empirical evidence from china's wto accession. *Journal of Economic Behavior & Organization* 178. 820–839.

Liu, Mingwei. 2010. Union organizing in china: still a monolithic labor movement? *ILR Review* 64(1). 30–52.

Liu, Zhengwen & Hong Ma. 2021. Input trade liberalization and markup distribution: Evidence from china. *Economic Inquiry* 59(1). 344–360.

Lu, Yi, Yoichi Sugita, Lianming Zhu et al. 2019. Wage markdowns and fdi liberalization. *Hitotsubashi Institute for Advanced Study Discussion Paper HIES-E*$_8$3, $HitotsubashiUnversity, Tokyo.$

Lu, Yi, Zhigang Tao & Yijiang Wang. 2010. Union effects on performance and employment relations: Evidence from china. *China Economic Review* 21(1). 202–210.

Lu, Yi & Linhui Yu. 2015. Trade liberalization and markup dispersion: evidence from china's wto accession. *American Economic Journal: Applied Economics* 7(4). 221–53.

Macedoni, Luca. 2021. Monopsonistic competition, trade, and the profit share. *The Scandinavian Journal of Economics* 124(2). 488–515.

Macedoni, Luca & Vladimir Tyazhelnikov. 2024. Oligopoly and oligopsony in international trade. *Canadian Journal of Economics/Revue canadienne d'économique* 57(2). 401–429.

Macedoni, Luca, Mingzhi Xu & Robert C Feenstra. 2020. Large firms in retail markets: Multiple products for heterogeneous consumers. *Available at SSRN 3475289* .

MacKenzie, Gaelan. 2021. Trade and market power in product and labor markets. *Technical Report, Bank of Canada* .

Manning, Alan. 2003a. *Monopsony in motion: Imperfect competition in labor markets*. Princeton University Press.

Manning, Alan. 2003b. The real thin theory: monopsony in modern labour markets. *Labour Economics* 10(2). 105–131.

Manning, Alan. 2021. Monopsony in labor markets: A review. *ILR Review* 74(1). 3–26.

Mayneris, Florian, Sandra Poncet & Tao Zhang. 2018. Improving or disappearing: Firm-level adjustments to minimum wages in china. *Journal of Development Economics* 135. 20–42.

Melitz, Marc J. 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* 71(6). 1695–1725.

Meng, Xin. 2012. Labor market outcomes and reforms in china. *Journal of Economic Perspectives* 26(4). 75–102.

Mertens, Matthias. 2020. Labor market power and the distorting effects of international trade. *International Journal of Industrial Organization* 68. 102562.

Midrigan, Virgiliu & Daniel Yi Xu. 2014. Finance and misallocation: Evidence from plant-level data. *American Economic Review* 104(2). 422–58.

Morlacco, Monica. 2019. Market power in input markets: Theory and evidence from french manufacturing. *Unpublished, March* 20. 2019.

Peters, Michael. 2020. Heterogeneous markups, growth, and endogenous misallocation. *Econometrica* 88(5). 2037–2073.

Pham, Hoang. 2023. Trade reform, oligopsony, and labor market distortion: Theory and evidence. *Journal of International Economics* 103787.

Qian, Yingyi. 2017. *How reform worked in china: The transition from plan to market*. MIT Press.

Rabinovich, Stanislav & Ronald Wolthoff. 2022. Misallocation inefficiency in partially directed search. *Journal of Economic Theory* 206. 105559.

Restuccia, Diego & Richard Rogerson. 2008. Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics* 11(4). 707–720.

Rodriguez-Lopez, Antonio & Miaojie Yu. 2024. All-around trade liberalization and firm-level employment: Theory and evidence from china. *Review of International Economics* 32(2). 328–370.

Rubens, Michael. 2023. Market structure, oligopsony power, and productivity. *American Economic Review* 113(9). 2382–2410.

Rubens, Michael, Yingjie Wu & Mingzhi Xu. 2024. Exploiting or augmenting labor? *Working Paper* .

Tian, Yuan. 2024. International trade liberalization and domestic institutional reform: Effects of wto accession on chinese internal migration policy. *The Review of Economics and Statistics* .

Topalova, Petia. 2010. Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india. *American Economic Journal: Applied Economics* 2(4). 1–41.

Tortarolo, Dario & Roman D Zarate. 2018. Measuring imperfect competition in product and labor markets. an empirical analysis using firm-level production data .

Trottner, Fabian. 2023. Unbundling market power .

Wang, Feicheng, Krisztina Kis-Katos & Minghai Zhou. 2020. Trade liberalization and the gender employment gap in china. *Available at SSRN 3667557* .

Wu, Liangjie. 2020. *Partially directed search in the labor market*: The University of Chicago dissertation.

Xu, Mingzhi. 2020. Globalization, the skill premium, and income distribution: the role of selection into entrepreneurship. *Review of World Economics* 156(3). 633–668.

Yao, Yang & Ninghua Zhong. 2013. Unions and workers' welfare in chinese firms. *Journal of Labor Economics* 31(3). 633–667.

Yeh, Chen, Claudia Macaluso & Brad Hershbein. 2022. Monopsony in the us labor market. *American Economic Review* 112(7). 2099–2138.

Yu, Miaojie. 2015. Processing trade, tariff reductions and firm productivity: Evidence from chinese firms. *The Economic Journal* 125(585). 943–988.

Zhan, Yubo, Jun Zhang & Wei Xu. 2012. Whether collective bargaining improves wages?- evidence from chinese manufacturing firms. *Journal of World Economy (In Chinese)* 35. 63–83.

Appendix A Details on the Data Processing

Following Cai & Liu (2009), Brandt et al. (2012, 2014, 2017) and Yu (2015), we conducted the following data cleaning process:

- Observations with missing key financial variables (such as total assets, net value of fixed assets, sales and gross value of the firm's output) were excluded
- Firms with fewer than eight workers were dropped from the sample
- Following the basic rules of the Generally Accepted Accounting Principles, we eliminate the observations that met any of the following criteria:
  - Liquid assets were greater than total assets
  - Total fixed assets were greater than total assets
  - The net value of fixed assets was greater than total assets
  - The firm's identification number was missing
  - There was an invalid time of establishment (e.g., the opening month was later than December or earlier than January).

In the ASIF data, there exist some trading companies that do not produce (Ahn et al., 2011). Following Brandt et al. (2017), we deleted these trading companies by identifying key words in their firm names. Moreover, the ASIF database includes mining industries; manufacturing industries; and electricity, gas, and water production and supply industries. We only retained firms in the manufacturing industry and omitted the other two types of firms.

Since the ASIF data do not report the actual capital stock of the company, we used the method of Brandt et al. (2012) to convert the book value of capital into the comparable actual capital stock. Meanwhile, the China Industrial Classification (CIC) 4-digit code was adjusted to be consistent over time and the nominal variables, such as output value, sales value, and intermediate input value, were converted into real variables using the deflator provided by Brandt et al. (2012).

We omitted observations on Tobacco (CIC2, 16) due to the lack of observations. The production function estimations were conducted at the CIC-2 level which implicitly implies that firms share similar production functions within each CIC-2 industry. As a result, we dropped other manufacturing industry (CIC2, 43) from our sample.

Appendix B Additional Figures and Tables

Figure B1: Evolution of Working Hours and Labor Income Share of China between 1998 and 2007

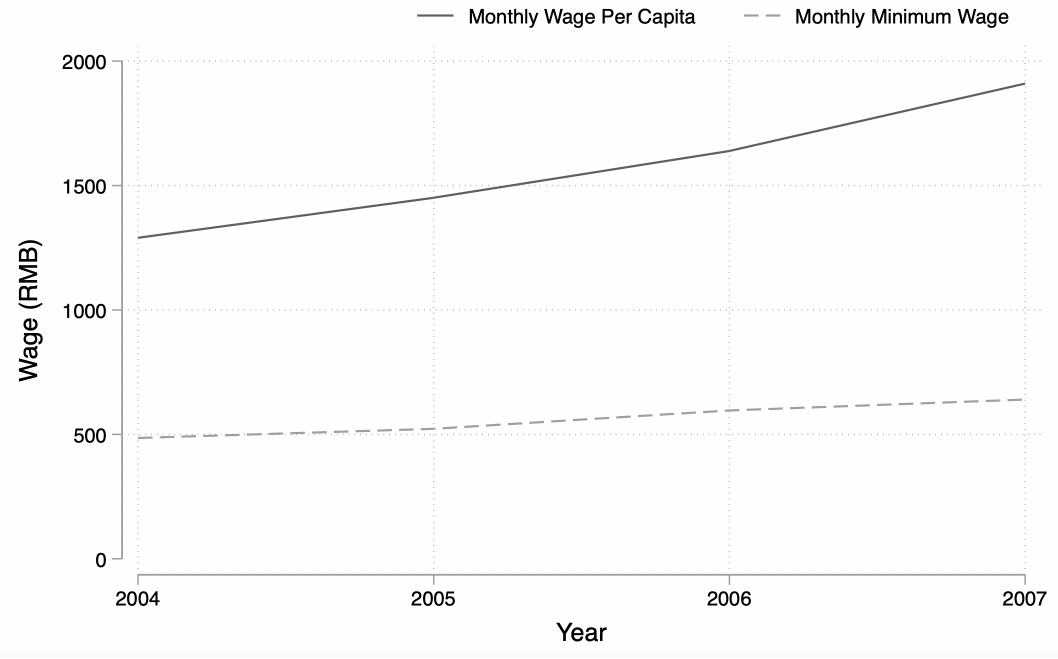

Figure B2: Trends in Minimum and Average Wages in Manufacturing Firms

Table B.1: Summary Statistics for High Union Industry and Low Union Industry

	High Union Group		Low Union Group		Differences	
Variables	N	Mean			Mean	t-Value
		Classification by Average Union Expenditure per Capita				
Input Tariff	153	0.067	268	0.066	0.001	0.460
Output Tariff	153	0.101	268	0.105	0.004	0.498
		Classification by Share of Firms with Established Unions				
Input Tariff	183	0.065	238	0.068	0.003	1.147
Output Tariff	183	0.097	238	0.108	0.011	1.634

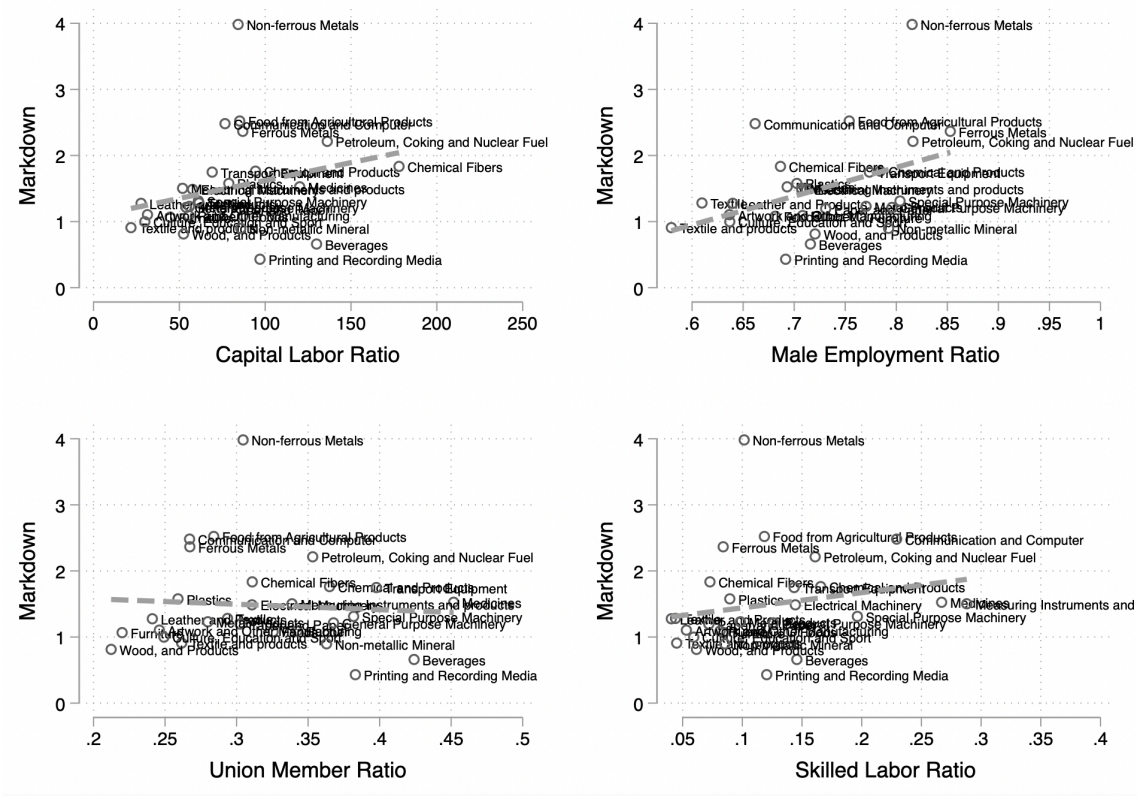

Figure B3: Labor Market Power and Industry Characteristics

Note: The data comes from 2004 ASIF, which provides detailed information about the employment characteristics of firms. The skilled labor ratio is defined as the ratio between the number of workers with college degree or above and the number of all workers. The male employment ratio is defined as the ratio between the number of male workers and the number of all worker. The union number ratio is the percent of workers enrolled in the union. Capital labor ratio is the capital per capita.

Table B.2: The Relationship Between Firms' Markdown, Skilled Labor Ratio and Trade Liberalization

Dependent Variables	(1) ln(Markdown)	(2) Skill Labor Ratio
Skill Labor Ratio	0.503***	
	(0.062)	
Input Tariff		0.284
		(0.235)
Output Tariff		-0.330***
		(0.079)
Control	Yes	Yes
CIC-4 FE	Yes	No
Province FE	Yes	Yes
Observations	241,522	241,522
Adjusted R-squared	0.449	0.198

Note: Robust standard errors in column (1) and (2) clustered at the CIC-2-level and CIC-4 level are in parentheses, respectively. ***, **, * denote significance at the 1%, 5%, 10% levels. The control variables include total factor productivity (in log), total output (in log), capital-labor ratio (in log), and wage per capita (in log). We use the share of workers with education above high school, including those with master, graduate and junior college degrees, to capture firms' skilled labor ratio.

Table B.3: The Relationship Between Firms' Markdown and Intermediate Input-Labor Ratio

Dependent Variables	Within Firms		Across Firms	
ln(Markdown)	(1)	(2)	(3)	(4)
ln(M/L)	0.667***	0.664***	0.729***	0.728***
	(0.001)	(0.001)	(0.001)	(0.001)
Control	No	Yes	No	Yes
Firm FE	Yes	Yes	No	No
CIC4-Year FE	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
Observations	1,781,528	1,781,528	1,907,887	1,907,887
Adjusted R^2	0.851	0.851	0.732	0.745

Note: Robust standard errors clustered at the firm-level are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels. The control variables include total factor productivity (in log), exporting firm indicator, State-owner enterprise indicator and foreign invested firm indicator.

Table B.4 reports the average of estimated output elasticity of the production function at the CIC-2 industry level calculated by ACF method (Cobb-Douglas specification). The mean values of the average output elasticities of labor, capital and intermediate inputs are around 0.07, 0.04, and 0.85, respectively.

Table B.4: Average Output Elasticity by CIC-2 Sector (ACF, Cobb-Douglas Specification)

Industry	No.obs.	β_L	β_K	β_M	RTS
13 Food from Agricultural Products	117,337	0.06	0.04	0.85	0.95
14 Foods	47,219	0.06	0.04	0.88	0.98
15 Beverages	32,793	0.03	0.02	0.89	0.94
17 Textile	162,311	0.07	0.03	0.86	0.96
18 Textile and products	92,868	0.09	0.04	0.80	0.93
19 Leather and Products	46,210	0.08	0.02	0.83	0.93
20 Wood, and Products	41,812	0.04	0.02	0.89	0.95
21 Furniture	22,315	0.07	0.03	0.85	0.95
22 Paper and Paper	57,176	0.06	0.03	0.87	0.96
23 Printing and Recording Media	40,234	0.04	0.02	0.83	0.89
24 Culture, Education and Sport	25,481	0.08	0.04	0.81	0.93
25 Petroleum, Coking and Nuclear Fuel	16,827	0.05	0.03	0.87	0.96
26 Chemical and Products	140,435	0.07	0.04	0.86	0.97
27 Medicines	40,905	0.09	0.06	0.82	0.97
28 Chemical Fibers	9,779	0.06	0.03	0.92	1.01
29 Rubber	23,021	0.07	0.05	0.84	0.96
30 Plastics	89,596	0.08	0.05	0.83	0.96
31 Non-metallic Mineral	165,781	0.06	0.04	0.88	0.98
32 Ferrous Metals	46,040	0.06	0.03	0.91	1.00
33 Non-ferrous Metals	34,267	0.08	0.03	0.88	0.99
34 Metal Products	103,756	0.07	0.04	0.86	0.97
35 General Purpose Machinery	146,404	0.08	0.05	0.85	0.99
36 Special Purpose Machinery	81,070	0.09	0.07	0.85	1.01
37 Transport Equipment	92,192	0.11	0.07	0.84	1.03
39 Electrical Machinery	114,855	0.08	0.04	0.86	0.98
40 Communication and Computer	64,512	0.17	0.08	0.80	1.05
41 Measuring Instruments and products	27,326	0.12	0.04	0.81	0.97
42 Artwork and Other Manufacturing	37,422	0.08	0.03	0.84	0.95

Following the method of Lu & Yu (2015), we identify the determinants of the input and output tariffs in 2001 at the CIC-4 level, including political factors (output shares of state-owned enterprises (SOEs), output share of other domestic firms, total employment in log, and employment growth rate over the past several years), economic factors (average wage per worker in log, capital-labor ratio in log, value-added ratio, and industry age), and industrial policy (export intensity). Tables B.5 and B.6 display the estimation results for input and output tariffs, respectively. Four variables have significant impacts on both input and output tariffs in 2001: (1) output share of SOEs, (2) output share of other domestic firms, (3) average wage per worker in log, and (4) export intensity.

Table B.5: Determinants of Input Tariffs in 2001

Dependent variables: Input tariff (2001)	Political (1)	Economic (2)	Industrial policy (3)
Output shares of SOEs (2001)	-0.033***	-0.052***	-0.061***
	(0.010)	(0.013)	(0.014)
Output shares of other domestic firms (2001)	-0.049***	-0.076***	-0.090***
	(0.010)	(0.011)	(0.013)
Log total employment (2001)	-0.002*	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Employment growth rate (98-01)	-0.027*	-0.012	-0.013
	(0.014)	(0.013)	(0.013)
Log average wage per worker (2001)		-0.042***	-0.041***
		(0.007)	(0.007)
Log capital-labor ratio (2001)		0.010**	0.006
		(0.004)	(0.004)
Value-added ratio (2001)		-0.014	-0.024
		(0.031)	(0.031)
Industry age (2001)		0.001	0.001
		(0.000)	(0.000)
Export intensity (2001)			-0.017***
			(0.006)
Observations	521	521	521
Adjusted R^2	0.042	0.101	0.108

Note: Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels.

Recall that, Figure 3 in the main text shows that the reduction in tariffs between 2001 and 2007 has a positive correlation with the level of tariffs in 2001. Hence, the regression results in Tables B.5 and B.6 are reasonable, for instance, industries with higher SOE output as a share of domestic firms' output experienced less tariff reduction after China's WTO accession.

Table B.6: Determinants of Output Tariffs in 2001

Dependent variables: Output Tariff (2001)	Political (1)	Economic (2)	Industrial policy (3)
Output shares of SOEs (2001)	-0.084***	-0.122***	-0.152***
	(0.029)	(0.039)	(0.041)
Output shares of other domestic firms (2001)	-0.121***	-0.164***	-0.208***
	(0.027)	(0.027)	(0.034)
Log total employment (2001)	-0.001	-0.005	-0.005
	(0.003)	(0.003)	(0.003)
Employment growth rate (98-01)	-0.073**	-0.046	-0.049
	(0.032)	(0.033)	(0.032)
Log average wage per worker (2001)		-0.096***	-0.094***
		(0.019)	(0.019)
Log capital-labor ratio (2001)		0.029***	0.019*
		(0.011)	(0.011)
Value-added ratio (2001)		0.088	0.059
		(0.094)	(0.094)
Industry age (2001)		0.001	0.000
		(0.001)	(0.001)
Export intensity (2001)			-0.052***
			(0.017)
Observations	521	521	521
Adjusted R^2	0.031	0.075	0.083

Note: Robust standard errors are in parentheses. ***, **, * denote significance at the 1%, 5%, 10% levels.

Appendix C Firm-Level Equilibrium

The optimization problem of each firm is to choose the quantities of the input and the output to maximize profits, subject to two constraints: labor supply (equation (5)), and the production function (equation (9)). Formally, firms' profit maximization problem is defined as follows:

$$\max_{q_{sj},m_{sj},l_{sjo}\ \forall o\in M_j} p_{sj}(q_{sj})q_{sj} - \left[\sum_{o=1}^{M_j} w_{sjo}(l_{sjo})l_{sjo}\right] - w^m m_{sj} \tag{C.1}$$

The Cobb-Douglas production function of an individual firm implies that the price of output can be expressed as the product of the markup and marginal cost. Thus, we have the following:

$$p_{sj} = \frac{1}{\rho_s}\left\{\frac{1}{\varphi_{sj}}\left[\frac{\prod_{o=1}^{M_j}\left(\frac{w_{sjo}\psi_{sjo}}{\gamma_o}\right)^{\gamma_o}}{1-\beta_s}\right]^{1-\beta_s}\left(\frac{w^m}{\beta_s}\right)^{\beta_s}\right\} \tag{C.2}$$

Solving firms' profit maximization problem, l_{sj} can be expressed as a function of productivity φ_{sj} and firm-level markdown ψ_{sj}, which is the following:

$$l_{sj} = \kappa_{sj}\psi_{sj}^{\frac{1-\beta_s\rho_s}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}}\varphi_{sj}^{\frac{-\rho_s}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} \tag{C.3}$$

where $\kappa_{sj} = \left\{\left(\frac{1}{P_s\rho_s}\right)\left(\frac{w^m}{\beta_s}\right)^{\beta_s\rho_s}\left[\frac{1}{(1-\beta_s)\gamma_o}\left(\frac{1}{L\lambda_{sj}}\right)^{\theta_j}\right]^{1-\beta_s\rho_s}{Q_s}^{\rho_s-1}\right\}^{\frac{1}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} > 0$. With $\beta_s \in (0,1)$, $\rho_s \in (0,1)$ and $\theta_j \in (0,1)$; thus, we can easily obtain $\frac{1-\beta_s\rho_s}{\rho_s-1+\theta_j(\beta_s\rho_s-1)} < 0$ and $\frac{-\rho_s}{\rho_s-1+\theta_j(\beta_s\rho_s-1)} > 0$. Hence, we have $\frac{\partial l_{sj}}{\partial \psi_{sj}} < 0$ and $\frac{\partial l_{sj}}{\partial \varphi_{sj}} > 0$. Given productivity, firms with more monopsony power employ fewer workers; and given monopsony power, more productive firms employ more workers. Similarly, we can also obtain the expression for m_{sj} as a function of productivity and monopsony power, which is the following:

$$m_{sj} = \chi_{sj}\kappa_{sj}\psi_{sj}^{\frac{\rho_s(1-\beta_s)}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}}\varphi_{sj}^{\frac{-\rho_s(\theta_j+1)}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} \tag{C.4}$$

where $\frac{\partial m_{sj}}{\partial \psi_{sj}} < 0$ and $\frac{\partial m_{sj}}{\partial \varphi_{sj}} > 0$. Given productivity, firms with monopsony power use less intermediate input. Given monopsony power, firms with higher productivity use more intermediate input.

Next, we consider the factor ratio of the firm. We can derive the intermediate input-labor ratio as a function of productivity and monopsony power:

$$\frac{m_{sj}}{l_{sj}} = \chi_{sj}\psi_{sj}^{\frac{\rho_s-1}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}}\varphi_{sj}^{\frac{-\rho_s\theta_j}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} \tag{C.5}$$

where $\chi_{sj} = \left(\frac{1}{1-\beta_s}\right)\left(\frac{w^m\gamma_o}{\beta_s}\right)^{-1}\left(\frac{1}{L\lambda_{sj}}\right)^{\theta_j}{\kappa_{sj}}^{\theta_j} > 0$, $\frac{\partial(m_{sj}/l_{sj})}{\partial \psi_{sj}} > 0$ and $\frac{\partial(m_{sj}/l_{sj})}{\partial \varphi_{sj}} > 0$. Given productivity, firms with greater monopsony power use more of the intermediate input relative to labor. Notably, given monopsony power, the improvement in Hicks-neutral productivity induces an intermediate input-biased

production technology change. The intuition is that monopsonistic competition implies increasing marginal costs of labor. When productivity increases, the firm expands, and the relative price of labor with respect to the price of the intermediate input increases, which makes the latter preferable.

Here, we investigate the impact of monopsony power on the firm's output. Similarly, the output can be expressed as a function of productivity and monopsony power:

$$q_{sj} = \Delta_{sj} {\psi_{sj}}^{\frac{1-\beta_s}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} {\varphi_{sj}}^{-\frac{1+\theta_j}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} \tag{C.6}$$

where $\Delta_{sj} = \left[\left(\frac{1}{1-\beta_s}\right)\left(\frac{w^m\gamma_o}{\beta_s}\right)^{-1}\left(\frac{1}{L\lambda_{sj}}\right)^{\theta_j}\right]^{\beta_s} {\kappa_{sj}}^{\beta_s\theta_j+1} > 0$, $\frac{\partial q_{sj}}{\partial \psi_{sj}} < 0$ and $\frac{\partial q_{sj}}{\partial \varphi_{sj}} > 0$. Equation (C.6) implies that, given productivity, firms with monopsony power produce less and charge higher prices. Given monopsony power, a more productive firm produces more.

The first order conditions of the firm's profit maximization problem can be rearranged to obtain the following expression in terms of the marginal revenue product of the factors of production:

$$\text{MRPL}_{sj} = (1-\beta_s)\rho_s \frac{p_{sj}q_{sj}}{l_{sj}} = w_{sj}\psi_{sj} = \Lambda_{sj} {\psi_{sj}}^{\frac{\rho_s-1}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} {\varphi_{sj}}^{-\frac{\rho_s\theta_j}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} \tag{C.7}$$

$$\text{MRPM}_{sj} = \beta_s\rho_s \frac{p_{sj}q_{sj}}{m_{sj}} = w^m \tag{C.8}$$

where $\Lambda_{sj} = \frac{1}{\gamma_o}\left(\frac{1}{L\lambda_{sj}}\right)^{\theta_j} {\kappa_{sj}}^{\theta_j} > 0$. By definition, $\text{TFPR}_{sj} = p_{sj}$, $\text{TFPQ}_{sj} = p_{sj}\varphi_{sj}$.[28] Plugging equations (9), (C.7) and (C.8) into the expression for TFPR_{sj}, we have the following:

$$\begin{aligned} \text{TFPR}_{sj} = & \frac{1}{\rho_s}\left(\frac{\text{MRPM}_{sj}}{\beta_s}\right)^{\beta_s}\left(\frac{\text{MRPL}_{sj}}{1-\beta_s}\right)^{1-\beta_s} \\ \propto & \ {\psi_{sj}}^{\frac{(\rho_s-1)(1-\beta_s)}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} {\varphi_{sj}}^{-\frac{\rho_s\theta_j(1-\beta_s)}{\rho_s-1+\theta_j(\beta_s\rho_s-1)}} \end{aligned} \tag{C.9}$$

Equation (C.9) implies that, when productivity or monopsony power is held fixed, a change in the other one - higher productivity or larger monopsony power - results in a higher TFPR_{sj}.[29] To sum up, the firm-level analysis shows that markdown ψ_{sj} serves as a *sufficient statistics* of the effect of labor market power on firm-level variables. Specifically, monopsony power leads a firm to use less of the input, produce less output, and charge higher prices. More interestingly, an increase in monopsony power and Hicks-neutral productivity results in intermediate input-biased production technology change. In a competitive labor market, resource allocation is uniquely determined by productivity. In contrast, in a monopsonistic labor market, resource allocation is distorted by heterogeneous monopsony power, and misallocation shows up.

[28] TFPQ and TFPR refer to quantity-based and revenue-based total factor productivity respectively (Foster et al., 2008).

[29] If we assume away labor market power, i.e. $\forall s \in S, \forall j \in M_s,\ \theta_j = 0,\ \psi_{sj} = 1$. The expression of TFRP_{sj} becomes $\text{TFPR}_{sj} = \frac{1}{\rho_s}\left(\frac{w^m}{\beta_s}\right)^{\beta_s}\left[\frac{1}{(1-\beta_s)\gamma_o}\right]^{1-\beta_s} = \text{TFPR}_s$, which means there is no TFPR dispersion within industries, which is similar to Hsieh & Klenow (2009).

Appendix D Mathematical Derivation of Aggregate Total Factor Productivity

The first-order condition of firms' profit maximization problem can be rearranged to obtain l_{sj} and m_{sj} as the functions of MRPL_{sj} and MRPM_{sj}, respectively:

$$l_{sj} = \frac{(1-\beta_s)\rho_s p_{sj} q_{sj}}{\text{MRPL}_{sj}} = (1-\beta_s)\rho_s \frac{1}{\text{MRPL}_{sj}} \frac{p_{sj} q_{sj}}{P_s Q_s} P_s Q_s \tag{D.1}$$

$$m_{sj} = \frac{\beta_s \rho_s p_{sj} q_{sj}}{\text{MRPM}_{sj}} = \beta_s \rho_s \frac{1}{\text{MRPM}_{sj}} \frac{p_{sj} q_{sj}}{P_s Q_s} P_s Q_s \tag{D.2}$$

Hence, we can obtain the industry-level usage of intermediate inputs and labor as the following:

$$l_s = \sum_{j \in M_s} l_{sj} = (1-\beta_s)\rho_s P_s Q_s / \overline{\text{MRPL}}_s \tag{D.3}$$

$$m_s = \sum_{j \in M_s} m_{sj} = \beta_s \rho_s P_s Q_s / \overline{\text{MRPM}}_s \tag{D.4}$$

where

$$1/\overline{\text{MRPL}}_s = \sum_{j \in M_s} \frac{1}{\text{MRPL}_{sj}} \frac{p_{sj} q_{sj}}{P_s Q_s} \tag{D.5}$$

$$1/\overline{\text{MRPM}}_s = \sum_{j \in M_s} \frac{1}{\text{MRPM}_{sj}} \frac{p_{sj} q_{sj}}{P_s Q_s} \tag{D.6}$$

denote the reciprocal of the weighted average of the value of the marginal revenue product of labor and intermediate inputs within an industry, respectively.

Then we can express aggregate output as a function of l_s, m_s, and industry-level TFP:

$$Q = \prod_{s=1}^{S} {Q_s}^{\alpha_s} = \prod_{s=1}^{S} \left(\text{TFP}_s {m_s}^{\beta_s} {l_s}^{1-\beta_s} \right)^{\alpha_s} \tag{D.7}$$

As a result, we can express the industry-level TFP as the following:

$$\text{TFP}_s = \frac{Q_s}{{m_s}^{\beta_s} {l_s}^{1-\beta_s}} \tag{D.8}$$

Plugging equations (D.3) and (D.4) into equation (D.8), we can express industry-level TFP as:

$$\text{TFP}_s = \overline{\text{TFPR}}_s \frac{1}{P_s} \tag{D.9}$$

where

$$\overline{\text{TFPR}}_s = \frac{1}{\rho_s}\left(\frac{\overline{\text{MRPM}}_s}{\beta_s}\right)^{\beta_s}\left(\frac{\overline{\text{MRPL}}_s}{1-\beta_s}\right)^{1-\beta_s} \tag{D.10}$$

is a geometric average of the average marginal revenue product of intermediate input and labor in the industry.

By definition, we have $p_{sj} = \text{TFPR}_{sj}/\text{TFRQ}_{sj} = \text{TFPR}_{sj}/\varphi_{sj}$, together with the expression for the manufacturing industry-level price index; thus, we have

$$\frac{1}{P_s} = \left(\sum_{j\in M_s} p_{sj}^{\frac{\rho_s}{\rho_s-1}}\right)^{\frac{1-\rho_s}{\rho_s}} = \left[\sum_{j\in M_s}\left(\frac{\text{TFPR}_{sj}}{\varphi_{sj}}\right)^{\frac{\rho_s}{\rho_s-1}}\right]^{\frac{1-\rho_s}{\rho_s}} \tag{D.11}$$

Equation (D.9) together with equation (D.11) imply that:

$$\text{TFP}_s = \left[\sum_{j\in M_s} \varphi_{sj}^{\frac{\rho_s}{1-\rho_s}}\left(\frac{\overline{\text{TFPR}}_s}{\text{TFPR}_{sj}}\right)^{\frac{\rho_s}{1-\rho_s}}\right]^{\frac{1-\rho_s}{\rho_s}} \tag{D.12}$$

Equations (C.9) and (D.10) jointly imply that:

$$\frac{\overline{\text{TFPR}}_s}{\text{TFPR}_{sj}} = \left(\frac{\overline{\text{MRPM}}_s}{\text{MRPM}_{sj}}\right)^{\beta_s}\left(\frac{\overline{\text{MRPL}}_s}{\text{MRPL}_{sj}}\right)^{1-\beta_s} \tag{D.13}$$

$\text{MRPM}_{sj} = w^m$ does not vary with industry and firm; hence, we can simplify equation (D.6) and obtain that $\overline{\text{MRPM}}_s = \text{MRPM}_{sj} = w^m \equiv 1$.

Following Hsieh & Klenow (2009), assuming that φ_{sj}, ψ_{sj}, and w_{sj} are jointly log-normally distributed, there is a simple closed-form expression for industry-level aggregate TFP:

$$\begin{aligned}\log \text{TFP}_s = &\log\left(\sum_{j\in M_s} \varphi_{sj}^{\frac{\rho_s}{1-\rho_s}}\right)^{\frac{1-\rho_s}{\rho_s}} - \Gamma_{1s}\left[\text{var}\log w_{sj} + \text{var}\log\psi_{sj}\right] \\ &- \Gamma_{2s}\,\text{cov}(\log w_{sj}, \log\psi_{sj})\end{aligned} \tag{D.14}$$

where:

$$\Gamma_{1s} = \frac{(\beta_s\rho_s-1)(\beta_s-1)}{2(1-\rho_s)}, \Gamma_{2s} = \frac{(\beta_s\rho_s-1)(\beta_s-1)}{1-\rho_s}$$

If we assume there is the only variation in $\log\psi_{sj}$, equation (D.14) can be further simplified as:

$$\log \text{TFP}_s = \log\left(\sum_{j\in M_s} \varphi_{sj}^{\frac{\rho_s}{1-\rho_s}}\right)^{\frac{1-\rho_s}{\rho_s}} - \Gamma_{1s}\text{var}\log\psi_{sj} \tag{D.15}$$

In this case, the negative effect of monopsony power on industry-level TFP can be summarized as the variance in $\log\psi_{sj}$. In short, labor market markdown dispersion incurs an efficiency loss.

Appendix E Argument for Using Intermediate Input as Flexible Input

Our measurement of markdown follows the "production approach" and has been widely used in the literature. Yeh et al. (2022) provide a comprehensive summarization of the assumptions used in the "production approach". Briefly, the assumptions require the existence of at least one flexible input that satisfies the following: (1) no adjustment costs, (2) not subject to monopsony force, and (3) chosen statically. In this section, we provide arguments to validate the assumption that intermediate input markets are perfectly competitive and firms are price takers in this market.

First, the intermediate input is the preferred flexible input in the literature (Brooks et al., 2021; Caselli et al., 2021; Kusaka, 2023; Mertens, 2020; Pham, 2023; Yeh et al., 2022). Using intermediate input as the flexible input is consistent with the literature.[30]

Second, as pointed out by Pham (2023) and Yeh et al. (2022), the intermediate input market is more open to trade and firms source their input in the global market. As a result, it is harder for firms to obtain monopsony power in the global intermediate input market. Figure E1 shows the China's import share of intermediate input goods, capital goods, and consumption goods during our sample period. The trade data are from UN Comtrade, and the product category is identified using the Broad Economic Classification (BEC) (Rev. 4), where the correspondence table between HS codes and BEC codes is obtained from World Integrated Trade Solution (WITS). Clearly, imports of intermediate inputs account for a large proportion of China's total imports, at around 75% on average.

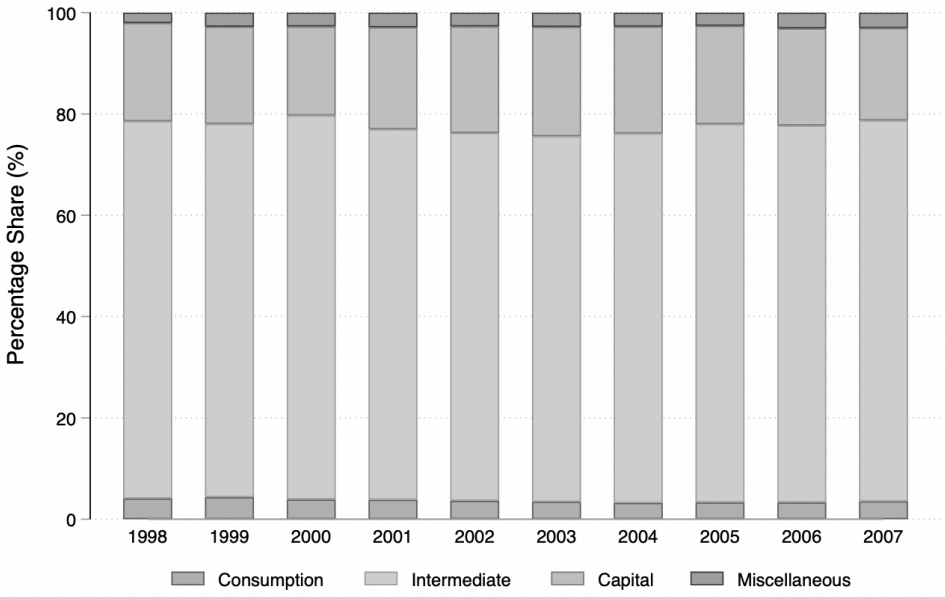

Figure E1: Import Share of Goods by Categories between 1998 and 2007

[30] De Loecker et al. (2018) use Belgian data to estimate firm-level product markups and the data can separate service intermediate inputs and goods intermediate input. They suggest that the goods intermediate input is more likely to be flexible.

Third, the intermediate input share is relatively large in Chinese manufacturing industry, which makes the markdown estimation using intermediate input as a flexible input less influenced by measurement error (Yeh et al., 2022). Meanwhile, following Yeh et al. (2022), we calculate the standard deviation of the input revenue share to capture the variability of inputss, and the results are presented in Table E.1. As expected, the intermediate input share is less volatile.[31]

Table E.1: The Variability of Inputs

Input	Mean	p25	Median	p75	SD
Labor	0.45	0.24	0.38	0.58	0.31
Intermediate	0.16	0.06	0.11	0.19	0.18
Capital	0.49	0.26	0.41	0.63	0.33

Note: Following Yeh et al. (2022), we calculate the standard deviation of normalized input revenue share over time. Each firm's input share is normalized by the mean value of its input share over time. We only keep firms which at least have three years of observation in our sample.

Fourth, to the best of our knowledge, there is no empirical work that documents systematic market power in the Chinese intermediate input market, except the study by Rubens (2023), which focuses on the tobacco market.[32] In our empirical analysis, we exclude the tobacco industry due to the violation of the assumption and the limited number of observations. Meanwhile, China initiated the raw material market reform in the 1990s to meet the needs of reforming and opening up and the WTO accession negotiation. As pointed out by Qian (2017), China adopted a dual-track approach to market liberalization and shifted from a plan-based economy to a market based economy. During the price reform in the 1990s, not only in the intermediate input market, but also in the product and labor markets, the share of planned-prices fell consistently. As a result, competition between firms in the intermediate input market increased, lending further credibility to our assumption of using intermediate input as the flexible input.[33]

Finally, as pointed out by Yeh et al. (2022), although the price-taker assumption in the intermediate input market does not hold, our estimation of labor market power would reflect the markdown for labor relative to the markdown for the intermediate input. Therefore, if firms possess monopsony power in the intermediate input market as well, our estimation of the markdown for labor serve as the lower bound for firms' labor market power.

[31] Yeh et al. (2022) propose that intermediate input is more suitable to serve as the flexible input than energy. However, the China's ASIF data provides no information on energy usage, which prevents us from using energy as flexible input to conduct a robustness check.

[32] The literature indicates that the state-owned enterprises monospsony power in the upstream market is concentrated in public utilities such as telecommunications, financial services, and water supply instead of intermediate inputs used for production purposes.

[33] We thank a referee for pointing this out. Please refer to chapter 2.4 in Qian (2017) for a detailed discussion of price reform in the product, intermediate input, raw material and labor markets.