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Wage Markdowns and FDI Liberalization*

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Abstract

This paper examines whether foreign direct investment (FDI) liberalization reduces firms' monopsony power in labor markets. We estimate firm-level wage markdown, wage over marginal revenue of labor, from China's production data and identify the causal effect of FDI liberalization on wage markdown, using China's regulation changes upon its accession to the World Trade Organization. Large and productive firms, state-owned firms, exporters, and foreign firms set narrower wage markdowns. FDI liberalization widened wage markdowns and decreased labor income share in value-added. These findings are contrast to classical monopsony theory based on concentration but consistent with modern theory based on search friction.

Keywords: Foreign direct investment, Monopsony, Wage, Search, Firm heterogeneity

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1 Introduction

Globalization has the potential to limit firms' market power by increasing competition. Liberalization of imports increases competition among sellers in goods markets, and liberalization of inward foreign direct investment (FDI) increases competition among buyers in factor markets. Although trade and FDI have played equally important roles in globalization, the literature has almost exclusively investigated the competition effect of trade liberalization on goods markets.¹² The competition effects of FDI liberalization on factor markets has attracted relatively little attention.

This paper examines the effect of inward FDI liberalization on domestic firms' monopsony power in labor markets. Our study is motivated by recent research in labor economics highlighting firms' monopsony power in labor markets.³ Employer concentration, worker's non-monetary preference for jobs and worker's search friction make labor supply curves to firms less elastic and allow firms to capture monopsonic rents by setting wages lower than the marginal revenue of labor (MRL). Wage markdown, the gap between wages and the MRL, determines not only the efficiency gains of FDI liberalization but also the distribution of FDI's gains to local workers. When foreign firms enter, local firms lose their employees and increase MRL. If wage markdown is constant, the wages at local firms should increase as much as the MRL increases, but when wage markdown is variable, the wage increase could be larger or smaller than the MRL increases.

We develop an empirical framework for analyzing the effect of inward FDI liberalization on wage markdown at domestic firms. We estimate firm-level wage markdown from Chinese manufacturing production data. Our estimation method is inspired by the price markup estimation by De Loecker and Warzynski (2012). Assuming that firms are price takers with respect to materials, we express wage markdown as a for-

¹For instance, during the 1990–2017 period, worldwide sales by foreign affiliates and worldwide exports have grown by roughly the same proportion (around 500%) (UNCTAD, 2018).

²See Tybout (2003), De Loecker and Goldberg (2014) and Van Biesebroeck and De Loecker (2016) for surveys of the literature.

³See, e.g., Manning (2003; 2011) and Ashenfelter, Farber, and Ransom (2010) for surveys.

mula relating wage expenditure, material expenditure, the revenue (or output) elasticity of labor, and the revenue (or output) elasticity of materials. We obtain the input expenditures from data and the output and revenue elasticities by estimating gross output production functions in a recent non-parametric method by Ghandi, Navarro and Rivers (2017). This method can be applied with typical production data available for many countries. We identify the causal effect of FDI liberalization on wage markdowns using variations in China's regulation on FDI inflow upon its accession to the World Trade Organization (WTO).

A main advantage of our framework is that it imposes no assumptions about labor market structure and the functional form of labor supply curves to individual firms. Such generality is crucial for our purpose. Theoretical predictions about the effect of FDI liberalization on wage markdowns are generally ambiguous and depend on labor market structures and the functional form of labor supply curves.⁴ If one estimates wage markdown from a structural model, the choice of a specific model and functional forms might result in assuming the sign of FDI's competition effect *a priori*. Our framework can avoid that potential pitfall.

We apply our framework to firm-level Chinese manufacturing production data spanning 1998 to 2007. In that period, Chinese labor markets generally lacked institutions protecting workers from firms' monopsony power (Gallagher, Giles, Park and Wang, 2015). Employment without formal written contracts was common. Collective bargaining and strikes were prohibited. Workers often had to accept wages unilaterally set by employers. In 2008, right after our sample period, China introduced a Labor Contract Law which improved worker protection. The estimated wage markdowns are consistent with this background. First, employers ubiquitously exercise monopsony powers. There are wage markdowns for 88% of the firms in our sample and the median firm pays only 25% of the MRL in wages. Second, markdowns are narrower for firms known for offering well-paying jobs, or "good jobs" in China: in particular

⁴In Appendix A2, we consider three canonical models of labor monopsony and shows that the sign of FDI's competition effect on wage markdown depends on the choice of model and functional form.

state owned enterprises (SOEs), foreign-owned firms, and exporters. Finally, narrow markdowns are associated with high productivity and large employment. These patterns tend to contradict the concentration theory of monopsony according to which it is large firms that exercise monopsony power, but they are consistent with the search frictional theory whereby high productivity firms offer higher wages to attract more workers.

Our second contribution is to estimate the causal effect of FDI liberalization on wage markdowns. Following Lu, Tao and Zhu (2017), we utilize plausibly exogenous relaxation of China's regulations on FDI inflow upon its WTO accession at the end of 2001 where China liberalized 112 of its 424 four-digit manufacturing industries. Following Topalova (2010) and Autor, Dorn and Hanson (2013), we map this industry-level FDI liberalization into county-level exposure to FDI liberalization based on county's initial employment across industries. We then conduct a simple difference-in-differences estimation of county's exposure to FDI liberalization on firm-level wage markdowns with firm fixed effects and year fixed effects. To address potential endogeneity, we control for (1) county's initial employment structure; (2) other policy reforms such as trade liberalization on output tariffs, input tariffs, and external tariffs, state owned enterprises reforms (SOE reforms), special economic zones; (3) inter-industry effects through vertical FDI linkages.

The estimation results are contrasting to the conventional wisdom. FDI liberalization induced the entry of foreign employers and enhanced competition among employers as expected. The conventional wisdom predicts that wage markdowns at incumbent firms would then narrow, but instead they actually widened. In a county with the mean level of exposure to FDI liberalization, incumbent firms reduced employment by 2.9% and increased MRL by 4.3%, as theory predicts. If wage markdown were constant as in traditional models, wages should have increased by the same 4.3%, but in fact they fell by 0.3% on average. The wage markdown therefore widened by 4.6%. Of course, the average wage in China grew steadily during this period. Precisely speaking, firms in counties with high exposure to FDI liberalization increased wage at almost the

same rate as firms in other counties, despite that the formers had labor shortage and increased MRL. A weighted regression using initial employment as weight shows that wage markdown for an average worker at incumbent firms expanded by 11.2 %. The economic gain of FDI inflow distributed to local workers is substantially smaller than the prediction of traditional models featuring constant wage markdown.

The expansion of wage markdown after FDI liberalization also contributes to a decline in labor income share in manufacturing value-added. We decompose changes in labor income shares in value-added of each firm to changes in four components: wage markdowns, price markups, labor elasticity and value-added revenue share. Then, we estimate the impact of FDI liberalization on each component and calculate its impacts on labor income share in value-added of the manufacturing sector. At the individual firm-level, a firm in a county with mean exposure to FDI liberalization reduced labor income share by 4.9%. Most of the effect comes from increases in firm's market power in labor and good markets. Wider wage markdown accounts for 84% of the effect, while wider price markup accounts for 17%. At the aggregate level, FDI liberalization brought 9% of the decline in aggregate labor income share in the manufacturing sector during 2001–2007. Wage markdown expansion accounts for 68% of the FDI effect.

Finally, we provide a theoretical explanation for our two main findings: (1) large and productive firms set narrower wage markdown; (2) FDI liberalization expands average wage markdown at incumbent firms. These two findings are contrast to a classical Cournot oligopsony model where employer concentration creates monopsony power, but they are consistent with a canonical model of search frictional monopsony by Burdett and Mortensen (1998) where workers search on the job. Burdett and Mortensen (1998) have demonstrated that large and productive firms may set narrower wage markdown to employ more workers and to earn profits from output markets. Our new finding is that when foreign firms with high productivity enter after FDI liberalization, the majority of domestic firms may expand their wage markdowns except for very high productive firms who can compete on wages with foreign firms. The intuition is simple. When foreign firms that pay higher wages enter, a marginal wage

increase by a domestic firm leads to fewer additional workers than before because such a marginal wage increase is insufficient to compete with high wage by foreign firms. In other words, those domestic firms that pay lower wage than foreign firms now face less elastic labor supply curves and widen wage markdown accordingly. On the other hand, for very productive firms that can pay higher wage than some of foreign entrants, a marginal increase in wage leads to more additional workers. Thus, these firms face more elastic labor supply curves and narrow wage markdown. We have confirmed this prediction about the heterogeneous change in wage markdown. We found that the top 19% of firms in terms of initial TFP before liberalization reduced their wage markdowns, while other firms increased them.

Related literature This paper contributes to the empirical literature on the effect of international competition on firm's market power. To our knowledge, our study is the first to empirically examine the effect of FDI liberalization on firm's monopsony power in labor markets. The literature has mostly focused on the impact of trade liberalization on price markups. Empirical studies using micro-level data include those of Levinsohn (1993), Harrison (1994), Krishna and Mitra (1998), Konings, Van Cayseele and Warzynski (2001), Chen, Imbs and Scott (2009), De Loecker, Goldberg, Khandelwal and Pavcnik (2016), and Feenstra and Weinstein (2016). Another strand of the literature conducts general equilibrium analyses such as those of Holmes, Hsu and Lee (2014), Edmond, Midrigan and Xu (2015), and Arkolakis, Costinot, Donaldson and Rodriguez-Clare (2018). Among these studies, our study closely follows the spirit of De Loecker et al. (2016) where the authors estimate price markups without imposing assumptions about market structure and functional forms and investigate the effect of import liberalization by India. De Loecker et al. (2016) found that import liberalization of final goods narrows output price markups (after controlling for the effect of import liberalization of intermediate goods). We found that FDI liberalization expands wage markdowns.

There is large literature about the impact of FDI on wage levels in host countries

(see Javorcik, 2013 and Hale and Xu, 2016 for surveys). The literature commonly finds that foreign firms pay higher wages than domestic firms (e.g., Aitken, Harrison and Lipsey, 1996; Heyman, Sjöholm and Tingvall, 2007). Several studies find the entry of foreign firms increases the wages paid by other firms in the labor market, including in China (e.g., Feenstra and Hanson, 1997; Hale and Long, 2011). Our focus is different. Our question is not whether wages increase or not, but whether wages increase as much as the MRL increases.

The current paper is related to recent research in labor economics estimating firm-level labor supply elasticities and monopsony power. Dal Bó, Finan and Rossi (2013), Falch (2010), Matsudaira (2014), Naidu, Nyarko and Wang (2016), and Staiger, Spetz and Phibbs (2010) estimate industry-level average markdowns. Dobbelaere, Kiyota and Mairesse (2015) and Dobbelaere and Kiyota (2018) classify industries in which firms exercise labor monopsony. Naidu, Nyarko and Wang (2016) is the closest to the current paper. The authors analyze the impact of an expansion of immigrant workers' outside options on (industry-level) wage markdowns, while we examine the effect of increased competition among employers induced by FDI liberalization.

The rest of the paper is organized as follows. Section 2 presents our estimation framework of wage markdowns. Section 3 discusses our data and China's FDI liberalization. Section 4 report empirical results. Section 5 concludes the paper.

2 Empirical Framework

2.1 Wage markdown measurement

Assume that firm j produces output Y_{jt} at time t with the gross production function:

$$Y_{jt} = F_{jt}(L_{jt}, K_{jt}, M_{jt}) \exp(\omega_{jt}) \quad (1)$$

where L_{jt} is labor, K_{jt} is capital, M_{jt} is materials and ω_{jt} is total factor productivity. Assume that firms are price takers of materials and that the first order condition for

profit maximization with respect to materials holds:

$$\frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial F_{jt}}{\partial M_{jt}} = P_{jt}^M \quad (2)$$

where $R_{jt}(Y_{jt}) = P_{jt}(Y_{jt})Y_{jt}$ is a firm's revenue as a function of its output Y_{jt} , $P_{jt}(Y_{jt})$, is an inverse demand function and P_{jt}^M is the price of materials. From (2), the marginal revenue of labor is then

$$MRL_{jt} \equiv \frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial F_{jt}}{\partial L_{jt}} = P_{jt}^M \left(\frac{\partial F_{jt}}{\partial M_{jt}} \right)^{-1} \frac{\partial F_{jt}}{\partial L_{jt}}. \quad (3)$$

The wage markdown η_{jt} , the ratio of wage to MRL, which can be simplified from (3) as

$$\eta_{jt} \equiv \frac{w_{jt}}{MRL_{jt}} = \left(\frac{w_{jt}L_{jt}}{P_{jt}^M M_{jt}} \right) \frac{\theta_{jt}^M}{\theta_{jt}^L} = \left(\frac{w_{jt}L_{jt}}{P_{jt}^M M_{jt}} \right) \frac{\tilde{\theta}_{jt}^M}{\tilde{\theta}_{jt}^L}, \quad (4)$$

where $\theta_{jt}^M \equiv \frac{\partial F_{jt}}{\partial M_{jt}} \frac{M_{jt}}{Y_{jt}}$ and $\theta_{jt}^L \equiv \frac{\partial F_{jt}}{\partial L_{jt}} \frac{L_{jt}}{Y_{jt}}$ are the output elasticities of materials and labor, respectively; $\tilde{\theta}_{jt}^M \equiv \frac{\partial R_{jt}}{\partial M_{jt}} \frac{M_{jt}}{R_{jt}}$ and $\tilde{\theta}_{jt}^L \equiv \frac{\partial R_{jt}}{\partial L_{jt}} \frac{L_{jt}}{R_{jt}}$ are revenue elasticities of materials and labor, respectively. The ratio of the revenue elasticities equals the ratio of the output elasticities because of the chain rule $\frac{\partial R_{jt}}{\partial Z_{jt}} = \frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial F_{jt}}{\partial Z_{jt}}$. A firm's total wage payment $w_{jt}L_{jt}$ and total material purchases $P_{jt}^M M_{jt}$ are available from typical production datasets. Revenue and output elasticities can be estimated from production data by applying production function estimation techniques.

Wage markdown can be interpreted as a measure of a firm's monopsony power. The profit maximization problem with respect to labor can be expressed as:

$$\max_{L_{jt}} R_{jt}(Y_{jt}) - w_{jt}(L_{jt})L_{jt} \text{ s.t. (1)} \quad (5)$$

where $w_{jt}(L_{jt})$ is the inverse labor supply function that the firm faces. The first order condition simplifies wage markdown as

$$\eta_{jt} = \frac{\varepsilon_{jt}}{\varepsilon_{jt} + 1} \leq 1. \quad (6)$$

where $\varepsilon_{jt} \equiv \frac{w_{jt}}{w'_{jt}(L_{jt})L_{jt}} \geq 0$ is the elasticity of the labor supply curve that firm j faces. When a firm is a price taker in the labor market, $\varepsilon_{jt} = \infty$, wages equal the MRL and the wage markdown is one. When ε_{jt} is finite, i.e., the firm-level labor supply curve to firm j is upward sloping, a firm sets its wage lower than its MRL. Notice that smaller ε_{jt} represents greater monopsony power. In the following, “wide” and “narrow” markdown express large and small monopsony power, respectively.

2.2 Discussion

Generality about market structure and functional forms The formula (4) is general about output and labor market structures and functional forms of demand and supply functions. Its derivation uses only the first order condition for materials (2). It does not impose any assumption about how wages and employment are determined. The firm-level inverse demand function $P_{jt}(Y_{jt})$ is consistent with all the major models of imperfect competition, and it allows various types of firm heterogeneity. When we interpret measured wage markdown we additionally assume that firms choose their labor following (5). The inverse labor supply function $w_{jt}(L_{jt})$ represents a reduced form relationship between wages and employment that is consistent with various models of imperfectly competitive labor market including search, bargaining, wage posting, etc.⁵ Although in problem (5) a firm chooses employment, it is straightforward to derive the same formula (4) from an equivalent problem where a firm chooses its wage level instead.

The generality of this formulation about labor market structure and functional forms is crucial for the study of FDI liberalization on wage markdown. Theoretical predictions about the effect of FDI liberalization on domestic firm’s wage markdowns vary among models depending on their functional form. In Appendix, we examine three canonical models of labor monopsony: the Cournot oligopsony model of employer concentration (e.g. Naidu et al. 2016), the Logit model of job differentiation

⁵For instance, Mortensen (2009), among others, has derived an upward-sloping inverse supply curve in a model in which a firm and workers bargain as Helpman and Itskohi (2008) have proposed.

(e.g. Card, Cardoso, Heining and Klein, 2018), and the Burdett-Mortensen model of worker's on the job search. The Cournot model predicts that FDI liberalization usually narrows wage markdown, while the other two models can predict that FDI liberalization widens wage markdown of domestic firms even with standard functional forms and parameters. This disagreement of prediction across models poses a challenge to our empirical study. If one estimates wage markdown from a structural model, the choice of a specific model may determine the sign of FDI's competition effect *a priori*.

The generality of the formula (4) does not, however, imply that its implementation is free from assumptions. The estimation of revenue and output elasticities requires some assumptions about data generating process and market structure. We choose an estimation method which is general about labor market structure and where the production function and labor supply curve are non-parametric.

The De Loecker-Warzynski price markup formula Our wage markdown estimation can be regarded as an application of price markup estimation by De Loecker and Warzynski (2012) (DLW price markup, hereafter). The generality of our markdown estimation about market structure and functional forms originates from the same virtue of the DLW price markup. Consider the following alternative derivation of (4). From $\partial R_{jt}/\partial Y_{jt} = MC_{jt}$ where MC_{jt} is marginal cost, wage markdown can be expressed as

$$\eta_{jt} = \frac{w_{jt}}{MC_{jt} \left(\frac{\partial F_{jt}}{\partial L_{jt}} \right)} = \mu_{jt} \frac{\alpha_{jt}^L}{\theta_{jt}^L},$$

where $\mu_{jt} \equiv P_{jt}/MC_{jt}$ is the output price markup and $\alpha_{jt}^L \equiv w_{jt}L_{jt}/R_{jt}$ is the wage payment share in revenue. If the firm is a price taker of materials, the DLW formula estimates price markup as $\mu_{jt} = \theta_{jt}^M/\alpha_{jt}^M$ where $\alpha_{jt}^M \equiv P_{jt}^M M_{jt}/R_{jt}$ is material expenditure share in revenue. Substituting this markup into the above equation yields wage markdown formula (4).

An important difference from the DLW markup formula is the data requirement.

Strictly speaking, the DLW markup formula requires output elasticities, while our wage markdown formula can be computed with either revenue elasticities or output elasticities. A typical production dataset reports only firm revenue without output price information. It is a common practice to use firm revenue as a proxy for output and to estimate revenue elasticities instead of output elasticities.⁶ Our wage markdown formula can be implemented with a typical production dataset without output price information.

Monopsony power for materials As in the DLW markup, our markdown formula requires firms to be price takers with respect to materials. If a firm holds monopsony power in materials, it charges the material price markdown $\delta_{jt} \equiv \frac{P_{jt}^M}{\frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial F_{jt}}{\partial M_{jt}}} \leq 1$. Then, (4) reduces to η_{jt}/δ_{jt} , labor monopsony power relative to material monopsony power. That will underestimate labor monopsony power (and overestimate η_{jt}). However, material monopsony is less likely to cause a major problem in our analysis. First, buyers usually hold monopsony power because sellers cannot easily find alternative buyers. This difficulty is particularly acute for workers who cannot easily move across labor markets and find buyers for their labor compared with sellers of materials. This is especially applicable in China where migration across regions are restricted while materials are freely tradable across regions. Second, as will be shown below, our estimates indicate significant labor monopsony, so there is little scope for underestimating labor monopsony. Finally, we use regional variations in exposure to FDI liberalization to estimate its effect on wage markdowns specifically because workers are not fully mobile across regions. On the other hand, since materials are tradable goods, the variations in material monopsony are more likely to be evident across industries rather than across regions. Thus as long as our region-level treatment is exogenous to regional industry structure (the identification assumption), our regression will consistently estimate the causal effect of FDI liberalization on wage markdown.

⁶Klette and Griliches (1996) and De Loecker and Warzynski (2012) discuss how to estimate output elasticities with such datasets.

Heterogeneous labor While we have considered the case that firms employ homogenous labor, firms normally employ workers of several skill types and set different wage markdowns for different skill types. If the wage and employment for each skill type can be observed as data, the formula (4) can easily be extended to measure wage markdown by type s of worker η_{jt}^s by replacing $w_{jt}L_{jt}$, $\tilde{\theta}_{jt}^L$, and θ_{jt}^L with the corresponding variables for each type s worker.

Typical production datasets like the one we use usually report only firm's total labor input without skill level breakouts. But even then, our markdown measure is still informative about a firm's monopsony power because workers' skills increase both the numerator (wages) and the denominator (MRL) simultaneously. To see this, suppose that workers of different types are perfectly substitutable. That is, the production function includes labor L_{jt}^* in an efficiency unit such that $L_{jt}^* = \sum_s \nu_{jt}^s L_{jt}^s$ where L_{jt}^s is type s labor and ν_{jt}^s is a skill converter. As we show in Appendix, in this case, a firm sets identical markdown for all types, $\eta_{jt} = \eta_{jt}^s$ for all s since they are perfectly substitutable. Our markdown formula (4) then correctly measures the firm's wage markdown. Even when workers of different types are imperfectly substitutable, our markdown measure (4) is the average markdown weighted by output elasticities such that $\eta_{jt} = \sum_s \left(\frac{\theta_{jt}^s}{\sum_{s'} \theta_{jt}^{s'}} \right) \eta_{jt}^s$ where θ_{jt}^s is the output elasticities of type s workers.

Non-profit maximizing firms Profit maximization may not be the objective for some firms such as state-own enterprises (SOE), firms in public sectors, and non-profit organizations. In China, SOE firms are large employers and often considered to care more about employment than about maximizing profits (e.g., Berkowitz, Ma and Nishioka, 2017). Suppose an SOE j seeks to maximize $\pi_{jt} + \gamma_j L_{jt}$ where π_{jt} is profits and $\gamma_j > 0$ is a weight for employment. Our formula (4) correctly estimates such an SOE's wage markdown η_{jt}^{SOE} since the first order condition for materials remains in the same form as (2). However, the relationship between wage markdown and labor supply elasticities changes. In the Appendix, we show that the wage markdown of SOE firms is

then

$$\eta_{jt}^{SOE} \equiv \frac{w_{jt}}{MRL_{jt}} = \left(\frac{\varepsilon_j}{\varepsilon_j + 1} \right) \left(\frac{1}{1 - \frac{\gamma}{w} \left(\frac{\varepsilon_j}{\varepsilon_j + 1} \right)} \right) > \left(\frac{\varepsilon_j}{\varepsilon_j + 1} \right). \quad (7)$$

If SOEs and private firms face similar labor supply elasticities, the SOEs would be expected to charge narrower wage markdown than the private firms.

2.3 Production Function Estimation

We estimate gross production function using a nonparametric estimation method by Gandhi, Navarro and Rivers (2017) (hereafter GNR). The literature of production function estimation has developed to cope with an endogeneity problem that firm's input choices may be correlated with unobservable total factor productivity (TFP). A series of seminal papers by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2015) have developed the so-called proxy approach using firm's factor usages as a proxy for TFP. Although the proxy approach can validly estimate value-added production function, GNR recently show that it is difficult to apply for that of gross output production function. When a standard set of assumptions for the proxy approach is satisfied, the gross output production function is not non-parametrically identifiable using either the proxy approach or the dynamic panel GMM approach.

GNR proposes an alternative method that additionally estimates the first order condition for materials (2). To utilize the first order condition, GNR's method has to specify output market structure, though it is still general about the labor market structure and non-parametric about production function and labor supply curve. Since output markups potentially affect wage markdowns, we use GNR's method for a monopolistic competitive output market where firms charge time-varying output markups (GNR, Appendix O5-4) and where markups can respond to FDI liberalization. Following De Loecker (2013), we also allow the stochastic process of productivity to depend on characteristics of the firms, industries and regions. Appendix A2 explains our imple-

mentation of GNR's method in detail.

2.4 Impacts of FDI liberalization

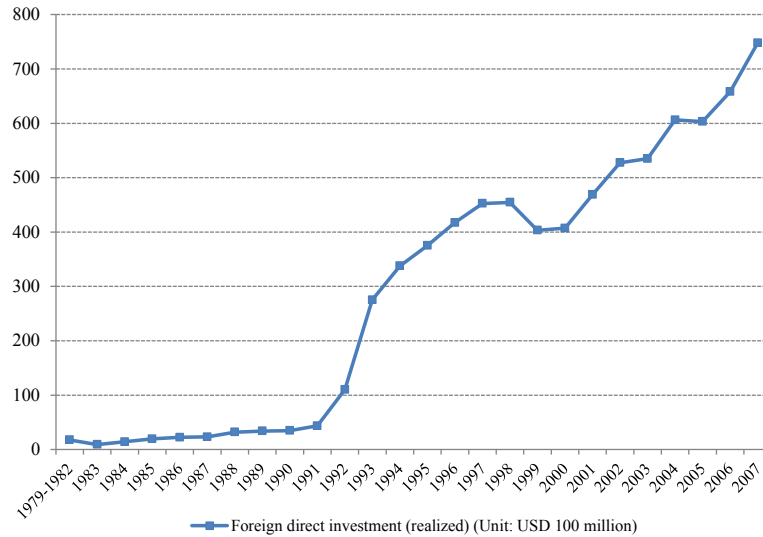
2.4.1 FDI regulation in China

In December 1978, the then leader of China, Deng Xiaoping, initiated an open door policy to promote foreign trade and investment. It dramatically altered the situation which had prevailed under rigid central planning. Before 1978, China hosted almost no foreign-invested enterprises, but during the 1980s, a series of laws on FDI and implementation measures were introduced.⁷ Foreign-invested enterprises enjoy preferential policies in terms of taxes, land use, and other matters, often in the form of policies for special economic zones. They have been expected to bring advanced technologies and management know-how to China and to promote China's integration into the world economy. As a result of these laws and implementation measures, China experienced rapid growth in FDI inflows from 1979 to 1991 (Figure 1). After Deng Xiaoping took a tour of Southern China in the spring of 1992 to revive a slowing economy, the FDI inflows to China grew even faster, reaching US\$ 27.52 billion in 1993.

Most significantly, the policies designated certaining industries in which FDI would be encouraged or discouraged. In June 1995, the central government published a *Catalogue for the Guidance of Foreign Investment Industries* (hereafter, the *Catalogue*). There were modifications made in 1997, but it became the government's unique guideline for regulating FDI inflows. Specifically, the *Catalogue* classified products into four categories: (i) those where FDI was supported, (ii) those where FDI was permitted, (iii) those where FDI was restricted, and (iv) those where FDI was prohibited. Importantly, the guideline was implemented uniformly nationwide. The central gov-

⁷In July 1979, a "Law on Sino-Foreign Equity Joint Ventures" was passed to attract foreign direct investment. In September 1983, the "Regulations for the Implementation of the Law on Sino-Foreign Equity Joint Ventures" was issued by the State Council of China; it was revised in January 1986, December 1987, and April 1990. In April 1986, the "Law on Foreign Capital Enterprises" was enacted. In October 1986, "Policies on Encouragement of Foreign Investment" was issued by the State Council of China.

Figure 1: Foreign Direct Investment (realized)



Datasource: China Foreign Economic Statistical Yearbook (various years)

ernment prohibited discretionary policies on FDI entry by regional governments.⁸

During the negotiations to join the WTO, China was asked to open itself up for trade and FDI. After China's entry into the WTO in November 2001, its central government substantially revised the Catalogue in March 2002 and relaxed FDI regulation to illustrate its commitment to WTO rules.⁹ In this study we exploit the plausibly exogenous relaxation of FDI regulations upon China's WTO accession at the end of 2001 to identify the FDI liberalization effect.

2.4.2 Locality-event DD approach

While FDI liberalization is nation-wide, firms are likely to exercise monopsony power within local labor markets. Following Topalova (2007) and Autor, Dorn and Hanson

⁸On May 4, 1997, the State Council issued the Termination of Unauthorized Local Examination and Approval of Commercial Enterprises with Foreign Investment, which forbid the location discretions about FDI entry regulations.

⁹There was another minor revision of the Catalogue in November 2004. The National Development and Reform Commission and the Ministry of Commerce jointly issued fifth and sixth revised versions of the Catalogue in October 2007 and December 2011, beyond the period studied.

(2013), we apply a locality-event difference-in-differences (DD) approach based on local labor market-level exposure to FDI liberalization. We use county as a unit of local labor market. That roughly corresponds to the US commuting zones used by Autor, Dorn and Hanson (2013).

We first map industry-level FDI liberalization into local labor market-level exposure to FDI liberalization. The industrial activity varies substantially among counties before China's WTO accession, so the sudden FDI regulation changes upon WTO accession impact the counties differently based on their initial employment structures. The county-level exposure to FDI liberalization FDI_{ct} is constructed as a local employment-weighted average of FDI regulation changes:

$$LIB_c \equiv \sum_s \frac{L_{cs1998}}{L_{c1998}} \times Liberalized_s \text{ and } FDI_{ct} \equiv LIB_c \times Post2002_t, \quad (8)$$

where s represents a four-digit manufacturing industry; $Liberalized_s$ is an indicator of whether inward FDI is liberalized for industry s ; $Post2002_t$ is a dummy variable indicating the post-WTO period, i.e., $Post2002_t = 1$ if $t \geq 2002$, and 0 if $t \leq 2001$; and L_{cs1998}/L_{c1998} is industry s 's share of employment in county c in 1998, the initial year of the sample period. The denominator L_{c1998} also includes employment in non-manufacturing sectors. By construction, FDI_{ct} takes its minimum value of zero if the county had no initial employment in liberalized industries and its maximum value one if all the county's initial employment is in liberalized industries.

The local labor market DD estimation has the following specification:

$$\ln \eta_{jct} = \alpha_j + \alpha_t + \phi FDI_{ct} + \mathbf{X}'_{ct} \Psi + \varepsilon_{jct}, \quad (9)$$

where j , c , and t represent firm, county and year, respectively. α_j is the firm fixed effect, controlling for all time-invariant differences across firms. Since most firms in the sample do not change their location, the firm fixed effects also control for all time-invariant difference among the counties such as geography, etc; α_t is the year fixed effect controlling for any annual shocks common to the counties such as business cy-

cles, monetary policies, exchange rate shocks, etc; and ε_{jct} is the error term. To isolate the effect of FDI regulation changes, we control for a vector of industry characteristics \mathbf{X}_{ct} (to be explained later) that may affect the outcome. To deal with potential heteroskedasticity and serial autocorrelation, the standard errors are clustered at the county level. The coefficient of interest ϕ captures the impact of county's exposure to FDI liberalization on wage markdown at an average firm. Since firms are heterogeneous in employment size, the effect on wage markdown to an average worker might be different. We therefore also conduct a weighted regression using employment share in 2001 as weights.

A crucial identification assumption about ϕ in equation (9) is that conditional on the covariates, the regressor of interest is uncorrelated with the error term, i.e.,

$$E[\varepsilon_{jct} | FDI_{ct}, \alpha_j, \alpha_t, \mathbf{X}'_{ct}] = E[\varepsilon_{jct} | \alpha_j, \alpha_t, \mathbf{X}'_{ct}]. \quad (10)$$

Since the variations in FDI_{ct} stem from variations in county's initial employment structure, one concern is that a county's initial employment structure may be correlated with unobserved time-varying county-level characteristics that affect wage markdowns. To address this concern, we include three sets of control variables in vector \mathbf{X}_{ct} . The first set of control variables is county's initial employment composition. We include interactions between year dummies and the share of employment in each of 15 sectors in county's total employment in 1998.¹⁰ The second set of control variables captures other on-going policy reforms around the time of FDI liberalization. First, to control for the effects of tariff reductions by China and its trading partners after China's WTO accession, we include county-level exposure to output tariffs, input

¹⁰The 15 sectors are 1. farming, forestry, animal husbandry and fishery; 2. mining and quarrying; 3. manufacturing; 4. production and supply of electric power, gas and water; 5. construction; 6. geological prospecting and water conservancy; 7. transport, storage, postal and telecommunication services; 8. wholesale and retail trade and catering services; 9. finance and insurance; 10. real estate; 11. social services; 12. health care, sports and social welfare; 13. education, culture and the arts, radio, film and television; 14. scientific research and polytechnical services; and 15. governments agencies, party agencies and social organizations.

tariffs, and external tariffs imposed by foreign countries.¹¹ Second, the restructuring and privatization of SOEs is another important policy reform in the early 2000s. To control for any differences in the SOE reforms across counties, we include county's share of SOEs in the total employment. Third, China set up special economic zones to attract foreign direct investment. We include an indicator for whether or not a county is in a special economic zone. Finally, county's exposure to FDI liberalization might be magnified by inter-industry vertical linkages. We therefore include county-level exposures to FDI liberalization in backward and forward industries as the third set of control variables.

3 Data

Panel Data on Industrial Firms The first dataset used in this study comes from the *Annual Survey of Industrial Firms* (ASIF), conducted by the National Bureau of Statistics of China for the 1998–2007 period.¹² The surveys cover all of the state-owned enterprises (SOEs) and non-SOEs with annual sales exceeding 5 million Chinese yuan (about US\$827,000). The number of firms covered in the surveys varies from approximately 162,000 to approximately 270,000. Though the title of ASIF includes “firms”, all information is reported on the firm-province level, so that the dataset is closer to a

¹¹The tariff data for HS-6 products are obtained from the World Integrated Trade Solution (WITS). By mapping HS-6 products to ASIF 4-digit industries through the concordance table published by China's National Bureau of Statistics, we are able to calculate simple average output tariff at the industry level. The input tariff is constructed as a weighted average of the output tariff, using the share of the inputs in the output value from the 2002 China's Input-Output Table as the weights. The export tariff is measured as a weighted average of the destination countries' tariffs on China's imports, using China's imports from each destination country as the weight. County's exposure to each tariff are calculated as a local employment-weighted average of the tariff as in (8).

¹²This is the most comprehensive and representative firm-level dataset in China, and the firms surveyed contribute the majority of China's industrial value-added. The dataset has been widely used by economic researchers in recent years, including Lu, Lu, and Tao (2010), Brandt, Van Biesebroeck, and Zhang (2012), and Khandelwal, Schott, and Wei (2013). In 2003, a new classification system for industry codes (GB/T 4754-2002) was adopted in China to replace the GB/T 4754-1994 system that had been used from 1995 to 2002. To achieve consistency in the industry codes over the period studied (1998–2007), we use the concordance table constructed by Brandt, Van Biesebroeck, and Zhang (2012).

plant-level dataset in contrast to the firm-level datasets in other countries.¹³ The dataset includes the basic information about each plant, such as its identification number, ownership structure, and industry affiliation, and the financial and operating information extracted from accounting statements, such as sales, employment, intermediate inputs, and the total wage bill, from which we construct variables for production function estimation. The total wage bill is measured as the sum of firm’s wage bills and supplementary compensation such as bonuses and insurance.¹⁴

Data on China’s FDI Regulations We classify each 4 digit industry into liberalized industries and non-liberalized industries, following Lu, Tao and Zhu (2017). We use the *Catalogue* to obtain information on FDI regulation changes of each industry upon China’s WTO accession at the end of 2001. Using the *Catalogue* for year t , we classify the products into four groups and assign an index of FDI regulation Reg_{st} for product s that could take one of four values: (i) the supported products $Reg_{st} = 1$ where FDI was supported; (ii) the permitted products $Reg_{st} = 2$ where FDI was permitted; (iii) the restricted products $Reg_{st} = 3$ where FDI was restricted; (iv) the prohibited products $Reg_{st} = 4$ where FDI was prohibited. Products not mentioned in the *Catalogue* are classified into the permitted category.

We then compare the 1997 and 2002 versions of the *Catalogue* and identify products into three groups: (i) liberalized products $\Delta Reg_s \equiv Reg_{s1997} - Reg_{s2002} > 0$; (ii) no change products $\Delta Reg_s = 0$; (iii) regulated products $\Delta Reg_s < 0$. Finally, we ag-

¹³According to Article 14 of the Company Law of the People’s Republic of China, however, for a company to set up a plant in a region other than its domicile, “it shall file a registration application with the company registration authority, and obtain the business license.” For example, Beijing Huiyuan Beverage and Food Group Co., Ltd. has six plants, located in Jizhong (Hebei Province), Youyu (Shanxi Province), Luzhong (Shandong Province), Qiqihar (Heilongjiang Province), Chengdu (Sichuan Province), and Yanbian (Jilin Province). Our data set accordingly counts them as six different observations belonging to six different regions.

¹⁴To convert the nominal values of output and input into real terms, we use industry-level ex-factory price indices for sales, and input price indices for intermediate inputs. Both price indices are provided by Brandt, Van Biesebroeck, and Zhang (2012). The real capital stock is constructed using the perpetual inventory method proposed by Brandt, Van Biesebroeck, and Zhang (2012). Specifically, we first calculate firm’s real capital stock in its founding year. Then we use firm’s fixed investment with depreciation rate of 9% to calculate its real capital stock in each year. The investment deflator is provided by Perkins and Rawski (2008).

Table 1: FDI entry after liberalization

	(1)	(2)	(3)
	1998–2001	2002–2007	Change (%)
<i>Panel A. Foreign equity share</i>			
Treatment	0.043	0.077	79.07
Control	0.069	0.104	50.72
<i>Panel B. Share of number of foreign firms</i>			
Treatment	0.131	0.161	22.78
Control	0.192	0.208	8.48

Note: the treatment (control) group refers to counties with high (low) FDI liberalization exposure in the initial year. Foreign equity share in Panel A and share of number of foreign firms in Panel B calculated over the pre-WTO 1998–2001 period, the post-WTO 2002–2007 period, and their percentage changes, respectively.

gregate the changes in FDI regulation from the *Catalogue's* product level to the ASIF industry level. The aggregation process leads to four possible scenarios: (i) FDI encouraged industries where all of the products are either liberalized or not changed; (ii) no change industries where all of the products are unchanged; (iii) FDI discouraged industries where all of the products are either more tightly regulated or unchanged; and (iv) mixed industries where some products are liberalized and others become more regulated. Among the 424 4-digit industries, 112 are FDI *encouraged industries*, 300 are *no-change industries*, 7 are FDI *discouraged industries* and 5 are *mixed industries*. We define an indicator of liberalized industries in (8) as follows: $Liberalized_s = 1$ if industry s belongs to *encouraged industries* and $Liberalized_s = 0$ otherwise.

Using information of county-level employment, we construct the county-level exposure to FDI liberalization FDI_{ct} . Its summary statistics are as follows: mean 0.32 with a standard deviation 0.21. The median falls at 0.28, the 25th percentile at 0.18, and the 75 percentile at 0.43. Table 1 shows FDI entry after the liberalization, comparing counties with above-mean exposure to FDI liberalization (the treatment group) and those with below-mean exposure (the control group). The treatment group shows a greater increase in FDI entry.

4 Empirical Results

4.1 Wage Markdowns and Firm Characteristics

Table 2 reports summary statistics on estimated revenue elasticities for each 2 digit industry. The substantial heterogeneity on elasticities within industries confirms the advantage of using a flexible production function. Overall, the estimated elasticities look reasonable. They are positive for most industries. Although the estimated capital elasticities are relatively small, this pattern has been observed in previous studies of Chinese firms using different estimation methods (e.g., Lu and Yu, 2015). It is thus the feature of the Chinese data rather than an artifact of the estimation method. We dropped three industries with negative median labor elasticities, which would imply negative wage markdowns. We also exclude the tobacco industry, which is heavily regulated.

Table 3 reports firm-level wage markdowns and output price markups. First of all, labor monopsony is ubiquitous in Chinese manufacturing industries. Column (1) reports median wage markdowns for each 2 digit industry. In our sample, 88% of the firms set wage markdowns smaller than one, and the median wage markdown for the entire sample is 0.25. Columns (3) and (4) report price markups. The median markup in the entire sample is 1.06, which is reasonably close to previous estimates of industry average markups ranging from 0.825 to 1.372. Lu and Yu (2015) make those estimates from the same dataset but with different methodology. Third, Columns (5) and (6) report median markdowns weighted by firm's employment, which suggests the markdown of an average worker. The weighted median markdown of 0.35 is slightly larger than the simple median of 0.25, suggesting that small employers exercise greater monopsony power. Finally, firm-level wage markdowns are heterogenous both across and within industries. Many industries show substantial heterogeneity in markdowns within industries.

Our estimates of wage markdown are comparable to estimates previously studied. Sokolova and Sorensen (2018) collect 700 labor supply elasticity estimates for

Table 2: Production Function Estimation

Industry	Revenue Elasticity With Respect to ...						Obs.
	Labor		Capital		Materials		
	(1)	(2)	(3)	(4)	(5)	(6)	
	Median	(p25, p75)	Median	(p25, p75)	Median	(p25, p75)	(7)
Food processing	0.35	(0.24, 0.46)	0.29	(0.22, 0.37)	0.69	(0.64, 0.73)	129,975
Food manufacturing	0.32	(0.21, 0.42)	0.35	(0.25, 0.45)	0.67	(0.63, 0.71)	52,333
Beverage manufacturing	0.46	(0.27, 0.62)	0.36	(0.24, 0.50)	0.63	(0.59, 0.68)	35,865
Textile industry	0.17	(0.09, 0.25)	0.27	(0.20, 0.33)	0.74	(0.70, 0.77)	170,353
Garments & other fiber products	0.24	(0.19, 0.28)	0.18	(0.13, 0.23)	0.70	(0.66, 0.75)	97,194
Leather, furs, down & related products	0.28	(0.24, 0.31)	0.21	(0.14, 0.27)	0.72	(0.68, 0.76)	48,522
Timber processing, bamboo, cane, palm fiber & straw products	0.19	(0.17, 0.22)	0.22	(0.17, 0.28)	0.71	(0.67, 0.74)	44,491
Furniture manufacturing	0.21	(0.18, 0.23)	0.17	(0.13, 0.21)	0.71	(0.67, 0.74)	23,656
Papermaking & paper products	0.27	(0.15, 0.37)	0.29	(0.22, 0.38)	0.73	(0.7, 0.75)	61,096
Printing industry	0.27	(0.24, 0.30)	0.72	(0.55, 0.90)	0.66	(0.6, 0.71)	43,597
Cultural, educational & sports goods	0.21	(0.19, 0.24)	0.20	(0.14, 0.25)	0.73	(0.69, 0.76)	26,550
Petroleum processing & coking	0.29	(0.18, 0.40)	0.30	(0.23, 0.40)	0.71	(0.67, 0.75)	17,977
Raw chemical materials & chemical products	0.29	(0.22, 0.35)	0.41	(0.31, 0.53)	0.71	(0.67, 0.74)	149,424
Medical & pharmaceutical products	-0.13	(-0.21, -0.05)	0.45	(0.36, 0.55)	0.61	(0.57, 0.66)	43,060
Chemical fiber	0.52	(0.38, 0.65)	0.33	(0.24, 0.47)	0.76	(0.73, 0.79)	10,304
Rubber products	0.01	(-0.01, 0.03)	0.30	(0.22, 0.39)	0.71	(0.68, 0.74)	24,205
Plastic products	0.40	(0.35, 0.43)	0.40	(0.29, 0.51)	0.73	(0.69, 0.76)	94,307
Nonmetal mineral products	0.12	(-0.6, 0.85)	0.30	(0.13, 0.47)	0.69	(0.65, 0.72)	175,768
Smelting & pressing of ferrous metals	0.06	(0.03, 0.10)	0.29	(0.22, 0.36)	0.74	(0.70, 0.77)	49,354
Smelting & pressing of nonferrous metals	0.00	(-0.03, 0.03)	0.30	(0.22, 0.38)	0.75	(0.70, 0.78)	36,339
Metal products	0.21	(0.14, 0.28)	0.40	(0.30, 0.50)	0.72	(0.69, 0.76)	109,990
Ordinary machinery	1.20	(1.00, 1.37)	0.26	(0.17, 0.35)	0.71	(0.68, 0.74)	153,252
Special purpose equipment	0.56	(0.53, 0.59)	0.42	(0.30, 0.53)	0.67	(0.63, 0.72)	85,860
Transport equipment	0.13	(0.09, 0.17)	0.46	(0.33, 0.58)	0.67	(0.6, 0.73)	98,891
Electric equipment & machinery	-0.06	(-0.08, -0.04)	0.33	(0.24, 0.41)	0.73	(0.69, 0.76)	120,020
Electronic & telecommunications equipment	0.31	(0.20, 0.40)	0.51	(0.36, 0.65)	0.67	(0.62, 0.73)	67,530
Instruments, meters, cultural & office equipment	0.07	(0.04, 0.11)	0.40	(0.29, 0.51)	0.65	(0.60, 0.70)	29,001
Other manufacturing	-0.22	(-0.25, -0.19)	0.22	(0.16, 0.27)	0.71	(0.66, 0.75)	39,526

Note: The table reports median, 25 percentile (p25) and 75 percentile (p75) of revenue elasticities with respect to labor, capital, and materials and the number of observations for each two digit level industry.

individual firms using 38 articles published from 1977 to 2018. According to their report on directly estimated 700 elasticities, the distribution of wage markdowns implied by (6) is that the median wage markdown is 0.52 with a 5% to 95% interval of $[-0.04, 0.80]$. Our estimated median markdown of 0.25 falls within the range of past estimates. Although it is lower than the median of previous estimates, that seems reasonable because the majority of past estimates are computed using data from developed countries which have better institutions protecting workers than those in China during our sample period.

Table 4 examines correlations of wage markdowns with firm characteristics, reporting the regression of wage markdown on logged TFPR in Column (1), on employment in Column (2), on dummy variables indicating state-ownership and foreign ownership in Column (3), and on a dummy variable indicating whether a firm is an exporter in Column (4). These regressions all include year fixed effects, with firm fixed effects included in Columns (1) and (2), and 4-digit industry fixed effects and county fixed effects in Columns (3) and (4). TFPR is revenue-based TFP (Foster, Haltiwanger, and Syverson, 2008), the residuals of revenue unexplained by inputs that may include not only physical TFP but also all positive shocks to firm revenue. Because such shocks tend to increase MRL, we use TFPR in this analysis.

Those firms that have narrower markdowns are considered to offer “good jobs” in China. They are high productivity firms, large employers, state-owned firms, foreign-owned firms and exporters. SOEs and foreign firms set 49% and 7% narrower markdowns, respectively, than domestic private firms. The SOEs’ narrower markdowns are consistent with (7)—SOEs care about employment as well as their profits.

Although those associations presented in Table 4 do not necessarily imply causality, the associations indicating that large and productive firms exercise less monopsony power might appear strange in view of classic monopsony theory of employer concentration predicting that a large firm will exercise monopsony power. They are, however, actually consistent with modern monopsony theory (Burdett and Mortensen, 1998) in which it is search friction that creates monopsony. Firms with high productivity pay

Table 3: Wage Markdowns and Price Markups

Industry	Wage Markdowns		Price Markups		Wage Markdowns (Weighted)	
	(1) Median	(2) (p25, p75)	(3) Median	(4) (p25, p75)	(5) Median	(6) (p25, p75)
Food processing	0.09	(0.04, 0.22)	1.38	(1.34, 1.43)	0.22	(0.09, 0.6)
Food manufacturing	0.22	(0.1, 0.48)	1.07	(1.04, 1.1)	0.43	(0.19, 0.99)
Beverage manufacturing	0.14	(0.06, 0.33)	1.13	(1.11, 1.18)	0.32	(0.13, 0.78)
Textile industry	0.45	(0.27, 0.73)	1.05	(1.03, 1.07)	0.32	(0.2, 0.49)
Garments & other fiber products	0.48	(0.32, 0.71)	2.95	(2.85, 3.02)	0.45	(0.29, 0.66)
Leather, furs, down & related products	0.34	(0.17, 0.56)	1.02	(1.01, 1.05)	0.59	(0.33, 1.14)
Timber processing, bamboo, cane, palm fiber & straw products	0.31	(0.17, 0.52)	1.15	(1.13, 1.17)	0.45	(0.25, 0.8)
Furniture manufacturing	0.36	(0.22, 0.56)	1.20	(1.19, 1.21)	0.40	(0.26, 0.58)
Papermaking & paper products	0.21	(0.11, 0.42)	1.02	(1.01, 1.03)	0.37	(0.18, 0.89)
Printing industry	0.38	(0.22, 0.66)	1.17	(1.15, 1.17)	0.45	(0.27, 0.75)
Cultural, educational & sports goods	0.48	(0.29, 0.77)	1.06	(1.05, 1.08)	0.82	(0.47, 1.55)
Petroleum processing & coking	0.12	(0.05, 0.28)	1.04	(1.02, 1.08)	0.30	(0.12, 0.86)
Raw chemical materials & chemical products	0.17	(0.08, 0.38)	1.07	(1.04, 1.09)	0.56	(0.22, 1.31)
Chemical fiber	0.08	(0.03, 0.16)	1.02	(1.01, 1.04)	0.18	(0.08, 0.46)
Rubber products	5.33	(3.24, 9.83)	7.36	(7.23, 7.5)	6.18	(3.57, 12.03)
Plastic products	0.16	(0.09, 0.29)	1.02	(1.02, 1.03)	0.28	(0.15, 0.53)
Nonmetal mineral products	0.09	(0.03, 0.25)	1.01	(1, 1.03)	0.15	(0.06, 0.44)
Smelting & pressing of ferrous metals	0.63	(0.39, 1.02)	7.86	(7.67, 8.12)	0.52	(0.33, 0.76)
Smelting & pressing of nonferrous metals	1.60	(0.82, 3.26)	1.03	(1.01, 1.05)	2.85	(1.42, 6.81)
Metal products	0.36	(0.21, 0.56)	1.00	(0.98, 1.02)	0.28	(0.16, 0.45)
Ordinary machinery	0.07	(0.03, 0.12)	1.04	(1.02, 1.07)	0.14	(0.07, 0.32)
Special purpose equipment	0.15	(0.08, 0.26)	1.03	(1, 1.07)	0.21	(0.12, 0.35)
Transport equipment	0.74	(0.4, 1.3)	5.46	(5.24, 5.74)	0.90	(0.46, 1.57)
Electronic & telecommunications equipment	0.30	(0.17, 0.52)	4.41	(4.31, 4.6)	0.19	(0.1, 0.35)
Instruments, meters, cultural & office equipment	1.38	(0.95, 2.13)	1.09	(1.04, 1.14)	1.72	(1.15, 2.59)
All industries	0.25	(0.1, 0.55)	1.06	(1.02, 1.19)	0.35	(0.17, 0.7)

Note: The table reports median, 25 percentile (p25) and 75 percentile (p75) of wage markdown, those of output price markup, and those statistics weighted by firm employment of wage markdown.

Table 4: Wage Markdown and Firm Characteristics

	(1)	(2)	(3)	(4)
Log wage markdown				
Log TFPR	0.047 (0.003)			
Log employment		0.278 (0.003)		
State owned dummy			0.489 (0.005)	
Foreign owned dummy			0.070 (0.004)	
Export dummy				0.04 (0.003)
Firm fixed effects	X	X		
County fixed effects			X	X
Industry fixed effects			X	X
Year fixed effects	X	X	X	X
Observations	1,308,875	1,292,740	1,235,508	1,235,508

Note: Standard errors are clustered at the firm level in parentheses.

higher wages, hire more workers and produce more output than firms with low productivity. In Section 5, we will show that wage markdown and employment can be both increasing in productivity.

Table 5 reports the regressions of logged wage markdown on county characteristics in 2000 together with log county's GDP per capita: on college graduate shares in population in Column (1), on manufacturing employment shares and SOE employment shares in manufacturing in Column (2), on the Herfindahl-Hirschman Index (HHI) of manufacturing employment in Column (3), and on county income per capita in Column (4). Wage markdown is narrower in counties with more college graduates, with more manufacturing and SOE employment, and with high concentration.

These results are also consistent with the job search theory. First, it may be easier for college graduates than others to change employers than for less educated workers, giving them lower search costs and wider outside options. If so, firms would set narrower markdowns for college graduates who have more elastic labor supply. Second, manufacturing firms and SOEs are considered to offer attractive jobs in China. In counties with plenty of such jobs, workers' better outside options may limit firms' monopsony power. Third, the positive relationship between wage markdown and the HHIs is at odds with the concentration theory, but not necessarily with the job search theory. Concentration usually plays no role in job search models, which often features a continuum of infinitely many firms. These patterns are robust after controlling for county GDP per capita.

4.2 FDI Liberalization

The DD estimation results are presented in Table 6. In addition to firm and year fixed effects, we step-wisely include a set of controls as elaborated in the previous section. The inclusion of these controls allows us to isolate the effect of FDI liberalization from other confounding factors such as the potential endogenous selection of open-up industries and other on-going policy reforms. Specifically, we include interactions between year dummies and county's initial sectoral employment share in Column (2).

Table 5: Wage Markdown and County Characteristics in 2000

Log wage markdown	(1)	(2)	(3)	(4)	(5)	(6)
College graduates share	2.638			4.764		
	(0.185)			(1.517)		
Manufacturing employment share		0.909			1.315	
		(0.065)			(0.155)	
SOE emp share		0.686			0.355	
		(0.036)			(0.052)	
Manufacturing employment HHI			0.347			0.549
			(0.087)			(0.107)
County GDP per capita				-0.030	-0.154	0.015
				(0.032)	(0.030)	(0.030)
Province fixed effects	X	X	X	X	X	X
Industry fixed effects	X	X	X	X	X	X
Observations	85,955	89,863	89,929	45,704	47,286	47,286

Note: Standard errors are clustered at the county level in parentheses.

Interactions between year dummies and other policy controls are additionally included in Column (3). Backward and forward FDI are added in the estimation reported in Column (4), which is our benchmark estimation.

The estimated coefficients of our regressor of interest, FDI_{ct} , are consistently negative and statistically significant at the 1% level. The negative coefficients indicate that the wage markdowns are wider and incumbent firms exercise greater monopsony power in counties more exposed to FDI liberalization. To see the economic magnitude, we rely on the estimates in column (4) and in Table 6 and the mean value 0.32 of FDI_{ct} at the county level. A firm in an average county decreases wage markdown by 4.6% ($\simeq 14.5\% \times 0.32$). As our sample covers 6 years after the FDI regulation changes, it can be translated into a 0.8% ($\simeq 4.6\%/6$) drop annually.

Columns (5) and (6) in Table 6 conduct robustness checks. Column (5) adds an interaction term of FDI_{ct} and a dummy on whether the year is 2001, one year before FDI liberalization. That is to check whether wage markdowns changes in anticipation

Table 6: FDI Liberalization and Wage Markdowns

Log wage markdown	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FDI Liberalization	-0.230 (0.038)	-0.151 (0.035)	-0.138 (0.034)	-0.145 (0.034)	-0.161 (0.038)	-0.145 (0.034)	-0.351 (0.069)
FDI Liberalization × Year2001 dummy					-0.046 (0.033)		
Initial employment struture		X	X	X	X	X	X
Other policy controls			X	X	X	X	X
Vertical FDI controls				X	X	X	X
Ownership controls						X	
Weighted by 2001 employment							X
Firm fixed effects	X	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X	X
Observations	970,416	970,416	970,416	970,416	970,416	970,416	469,466

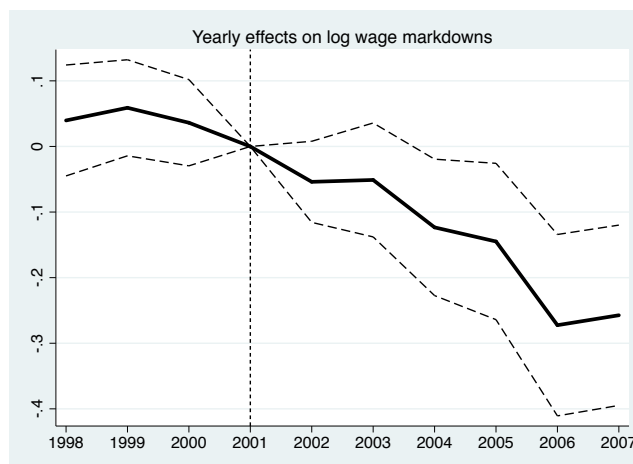
Note: Standard errors are clustered at the county level in parentheses. Initial employment structure include interactions between year dummies and county's employment share of 16 sectors in 2001. Other policy controls include: (1) county's exposures to tariffs (output tariffs, input tariffs, and tariffs by foreign countries); (2) the share of state-owned enterprises among firms in a county, (3) a dummy variable indicating whether a county is a special economic zone or not. Vertical FDI controls include county's exposure to FDI liberalization in backward and forward industries. Ownership control includes FIE dummy and SOE dummy. Column (7) reports weighted regression with employment in 2001 being the weight.

of the FDI liberalization. The coefficient of the interaction term is close to zero and statistically insignificant, which indicates there is no expectation effect. Column (6) includes SOE and foreign-invested enterprise dummies to control for firm's ownership structures and that produces virtually no change.

Our baseline regression estimates the effect of FDI liberalization on an average firm. To see the effect on an average worker, Column (7) conducts a weighted regression that uses firm's employment in 2001 as the weight. The coefficient becomes larger than the unweighted estimates. In an average county with mean FDI exposure, wage markdown for an average worker expands by 11.2% ($\simeq 35.1\% \times 0.32$).

Figure 2 plots yearly effects of FDI liberalization. We estimate a regression with baseline covariates in Column (4) of Table 6 and the interaction terms of LIB_c in (8) and year dummies instead of FDI_{ct} . Figure 2 reports the coefficients of the interaction terms with 95% confidence intervals. The negative effect of FDI liberalization becomes stronger in later years. It suggests that the discrepancy between wages and

Figure 2: Yearly Effects of FDI Liberalization on Wage Markdown



Note: the solid line expresses the coefficients of interaction terms of FDI liberalization and year dummies in the regression of log wage markdown with main regressors. The dashed lines express 95% confidence intervals.

MRL did not occur as a short-run adjustment process. It is a long run transition process from one equilibrium to another. Furthermore, it is apparent that in the pre-WTO period, the coefficients are stable around zero, which suggests that with our main control variables, counties highly exposed to FDI liberalization and other counties show quite similar trends. This alleviates the concern that our treatment and control groups are systematically different *ex ante*, lending support to our DD identifying assumption.

Next we investigate the mechanism behind the expansion of wage markdown. Because our dataset records firm-level wages, we obtain each individual firm's MRL as the ratio of wages to wage markdown. Theories commonly predict that the entry of foreign firms makes incumbent firms lose employees and increases their MRL. Columns (1) and (2) of Table 7 regress log employment and log MRL as a dependent variable on the main regressors in Column (4) of Table 6 and find evidence confirming this prediction. In an average county, incumbent firms reduced employment by 2.9% ($\simeq -9.0\% \times 0.32$) and increased their MRL by 4.3% ($\simeq 13.3\% \times 0.32$). If wage markdown is constant as in traditional models of FDI, workers should receive as much

as the increase in MRL. However, Column (3) regresses log wages on the same regressors, and it shows that the actual wage change was close to zero or even slightly negative. In an average county, wages at an average firm fell by 0.38% ($\simeq -1.2\% \times 0.32$). By construction, the coefficient ϕ from the wage markdown regression is equal to the coefficient ϕ from the wage regression in Column (3) minus the coefficient ϕ from the MRL regression in Column (2). Note that the small coefficient in Column (3) does not imply that wages were stable over the period. Instead, during 2001–2007, the average wages grew steadily at an average annual growth rate of 12%. Column (2) thus implies that firms with high exposures to FDI liberalization increased their wages only at the same speed as the national average even though they faced labor shortages and increases in MRL.

One might think that the wage stagnation is due to a drop in labor quality at incumbent firms. Wages might decrease relative to estimated MRL if high skilled workers move to new foreign firms and incumbent firms replace them with workers with low skills paying them lower wages. Column (4) checks this hypothesis by investigating the effect of FDI liberalization on the firm-specific component of TFPR (TFPRC), which removes industry-level demand shocks from TFPR. Since we do not control for labor quality when estimating the production function, a fall in labor quality should be reflected in a fall in TFPRC. The fact that the impact of FDI liberalization on TFPRC is small and insignificant does not support the hypothesis.

4.3 Labor Income Share in Manufacturing Value-added

The labor income share of GDP has been declining over the past decades in many countries (e.g. Karabarbounis and Neiman, 2014). The Chinese economy shows a similar trend: in our dataset, labor income share in the aggregate manufacturing value-added declined from 0.26 to 0.19 during 1998–2007.¹⁵ There is active ongoing research into

¹⁵The labor share in this dataset is smaller than those for other countries. Even if there is a systematic underestimation of labor shares, our DD estimation is still valid as long as the pattern of underestimation is not correlated with our treatment variable.

Table 7: Decomposition and Mechanism

	(1)	(2)	(3)	(4)
Dependent variables:	Log Employment	Log MRL	Log wages	Log TFPRC
FDI liberalization	-0.090 (0.031)	0.133 (0.034)	-0.012 (0.022)	-0.010 (0.055)
Initial employment structure	X	X	X	X
Other policy controls	X	X	X	X
Vertical FDI controls	X	X	X	X
Firm fixed effects	X	X	X	X
Year fixed effects	X	X	X	X
Observations	970,416	970,416	970,416	970,416

Note: Standard errors are clustered at the county level in parentheses. Initial employment structure include interactions between year dummies and county's employment share of 16 sectors in 2001. Other policy controls include: (1) county's exposures to tariffs (output tariffs, input tariffs, and tariffs by foreign countries); (2) the share of state-owned enterprises among firms in a county, (3) a dummy variable indicating whether a county is a special economic zone or not. Vertical FDI controls include county's exposure to FDI liberalization in backward and forward industries.

the causes of the labor share decline. Two candidates often mentioned are technological changes and a rise in firm's market power in goods markets. In the study of the latter candidate, for instance, Autor, Dorn, Katz, Patterson and Van Reenen (2017) investigate labor income share and industry concentration; De Loecker, Eeckhout and Unger (2018) examine output price markups following De Loecker and Warzynski (2012). These studies focus on firm's market power in good markets, but not in labor markets.

In theory, a rise in firm's monopsony power in the labor markets also contributes to a decrease in labor income share. As we show in Appendix, firm j 's labor income share in value-added can be decomposed as:

$$\ln \frac{w_{jt}L_{jt}}{VA_{jt}} = \ln \eta_{jt} - \ln \mu_{jt} + \ln \theta_{jt}^L - \ln \frac{VA_{jt}}{P_{jt}Y_{jt}} \quad (11)$$

where η_{jt} is the wage markdown, μ_{jt} is the output markups, θ_{jt}^L is the labor elasticity of the gross production function, and $VA_{jt}/P_{jt}Y_{jt}$ is the share of valued-added in to-

Table 8: FDI Liberalization and Labor Income Share

Dependent variables:	Log Labor Share	Log Markdown	Log Markup	Log Labor Elasticity	Log VA share
	(1)	(2)	(3)	(4)	(5)
FDI Liberalization	-0.175 (0.043)	-0.147 (0.037)	0.030 (0.015)	0.003 (0.018)	0.000 (0.026)
Initial employment structure	X	X	X	X	X
Other policy controls	X	X	X	X	X
Vertical FDI controls	X	X	X	X	X
Firm fixed effects	X	X	X	X	X
Year fixed effects	X	X	X	X	X
Observations	848,738	848,738	848,738	848,738	848,738

Note: Standard errors are clustered at the county level in parentheses. Initial employment structure include interactions between year dummies and county's employment share of 16 sectors in 2001. Other policy controls include: (1) county's exposures to tariffs (output tariffs, input tariffs, and tariffs by foreign countries); (2) the share of state-owned enterprises among firms in a county, (3) a dummy variable indicating whether a county is a special economic zone or not. Vertical FDI controls include county's exposure to FDI liberalization in backward and forward industries.

tal sales. Equation (11) shows that wider wage markdowns and wider price markups both tend to decrease labor income share. We have already seen that FDI liberalization tend to widen wage markdowns. This raises a question of how much FDI liberalization decreases labor income share by increasing firm's monopsony power in the labor market.

Table 8 examines the impact of FDI liberalization on firm-level labor income share in value-added and its four components in (11). The logs of labor income share and each component in (11) are regressed on the same set of covariates as in (9) and the fixed effects. Each column reports the coefficients of FDI_{ct} . The decomposition in (11) indicates that the coefficient in Column (1) should equal that in Column (2) minus Column (3) plus Column (4) and minus Column (5). First of all, FDI liberalization decreases labor income share in value-added. With a mean FDI_{ct} of 0.32, a firm in an average county reduces labor income share by 5.6% $\simeq 17.5 \times 0.32$. The change in wage markdown in Column (2) accounts for 84% of the effect, and the change in output markup in Column (3) for 17%. Columns (4) and (5) suggest that technology played little systematic role.

To see the aggregate economic magnitude, we conduct a simple counter-factual analysis about the aggregate labor income share in the manufacturing sector. We first

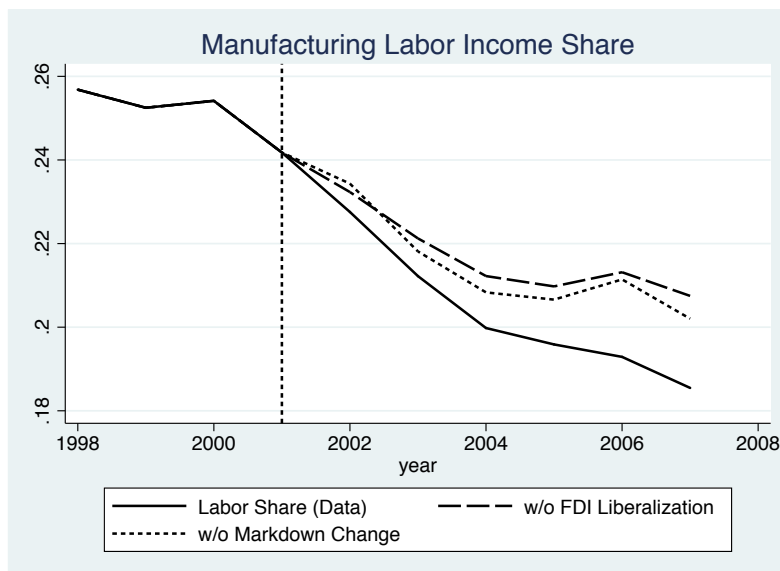
run the regressions in Table 8 including interaction terms of LIB_c and year dummies for the post-liberalization period. Based on the estimates, we calculate counter-factual labor income shares and the four components without FDI liberalization, i.e. $LIB_c = 0$, for each firm and each year. We assume that FDI liberalization does not change firm's value-added share in the industry. We then calculate the counter-factual aggregate labor income share in the manufacturing sector under two scenarios. In scenario 1, all four components in (11) are counter-factual ones without FDI liberalization; in scenario 2 all components except the markdown in (11) are counter-factual. Figure 3 shows these two scenarios with actual data. The figure shows that FDI liberalization may not be the main cause of the decline in labor income share, but it seems to accelerate the declining trend. From 2001 to 2007, the aggregate labor income share declined by 23.5% (5.6 points) from 0.242 to 0.185 in data. The counter-factual labor income shares would be 0.207 in scenario 1 and 0.202 in scenario 2. While FDI liberalization reduced the labor income share by 9% (2.2 points), the expansion of wage markdown alone reduced it by 7% (1.5 points). These rough estimates should be carefully interpreted, but they suggest that FDI liberalization accelerated the decline in labor income share by expanding wage markdowns.

4.4 An Explanation: Search Frictional Monopsony

The conventional wisdom suggests that monopsony power increases in firm size and that competition reduces monopsony power. We have found the exact opposite: large and productive firms tend to set narrower wage markdowns and FDI liberalization widens incumbent firms' wage markdowns. In Appendix, we show that these findings indeed contrast with a classical Cournot oligopsony model where employer concentration creates monopsony power. However, concentration is not the only reason for firm's monopsony power. In this section, we show that these findings are consistent with modern monopsony theory: a canonical model of Burdett and Mortensen (1998) where search frictions create monopsony power.

In the Burdett-Mortensen model, workers always search for better jobs even when

Figure 3: Labor Income Share in Manufacturing Value-added



Note: the solid line expresses labor income share in the aggregate manufacturing value-added in data. The dashed line expresses counter-factual labor shares without FDI liberalization. The dotted line expresses counter-factual labor shares when FDI liberalization changes other components of labor shares except wage markdown.

they are employed, so that workers may accept low wage jobs, hoping to move up to a better job in future. The worker's search on the job makes the labor supply curves of individual firms less elastic and allows firms to set wages lower than their MRL. This logic does not rely on either concentration or firm's size. Therefore, there is no guarantee that the entry of foreign firms would make labor supply curves more elastic.

We consider an original formulation of Burdett and Mortensen (1998). There exist continuums of homogenous workers with mass L and continuums of firms with mass N . Firms are heterogenous in productivity φ that follows distribution function $J(\varphi)$ with continuous support $[b, \varphi_{max}]$. Firms produce a numeraire good under perfect competition for labor and constant returns to scale technology.

The model infinitely repeats the following period game. First, each firm announces wage offer w that is common for its employees. Second, both employed and unemployed workers meet a new potential employer with Poisson rate λ . An unemployed worker accepts any offer with wage w higher than unemployment benefit b , while an employed worker only accepts a higher wage offer than the current wage. Third, firms produce goods. Fourth, workers leave their jobs with exogenous rate δ and become unemployed. The time discount rate of workers and firms is negligible so that they maximize their per-period payoffs.

In a steady state, there is a positive relationship between employment and wages, which represents the labor supply curve to an individual firm:

$$l(w) = \frac{Lk}{N[1 + k(1 - F(w))]^2} \text{ for } w \in [b, \bar{w}], \quad (12)$$

where $k \equiv \lambda/\delta$ and $F(w)$ is the distribution function of wage offers. The labor supply curve is upward sloping because a high-wage firm attracts workers from other firms as well as prevents its own workers from moving to other firms.

Firms maximize per-period profits, facing labor supply curves (12):

$$\max_w \pi(w, \varphi) \equiv \varphi l(w) - wl(w) \text{ subject to (12)}. \quad (13)$$

Supermodularity $\partial^2 \pi(w, \varphi) / \partial w \partial \varphi > 0$ implies that the equilibrium wage is increasing in productivity, $w'(\varphi) > 0$. The lowest wage is equal to the unemployment benefit $b = w(b)$. This positive sorting of wage and productivity implies that the wage distribution agrees with the productivity distribution: $F(w(\varphi)) = J(\varphi)$ for all φ .

We obtain equilibrium wage markdown as:

$$\eta(\varphi) = 1 - \left(\frac{\varphi - b}{\varphi} \right) \frac{\bar{L}(\varphi)}{L(\varphi)},$$

where $L(\varphi) = l(w(\varphi)) \equiv \frac{Lk}{N[1+k(1-J(\varphi))]^2}$ is an equilibrium employment at firm with productivity φ and $\bar{L}(\varphi) \equiv \frac{1}{\varphi - b} \int_b^s L(s) ds$ is the average employment among firms with productivity lower than φ . Wage markdown increases and narrows when $L(\varphi) / \bar{L}(\varphi)$ increases. This is intuitive, because a firm increases wages to attract workers from lower productive firms which set lower wages. Markdown can increase or decrease with productivity, depending on the productivity distribution J . For instance, when $J(\varphi) = \varphi$ is uniform, $\eta(\varphi) = \frac{k\varphi}{1+k}$ for $\varphi > 0$. In this case, larger and more productive firms set narrower markdowns, as we found in the data.

Inward FDI affects wage markdown by changing the productivity distribution of firms in the labor market. There is a robust empirical finding that foreign-owned firms are more productive and pay higher wages than domestic firms. Following these stylized facts, we model inward FDI liberalization as the entry of foreign firms with productivity support $[\varphi_{min}^F, \varphi_{max}^F]$ and $\varphi_{min}^F > b$. Inward FDI liberalization affects markdown by shifting productivity distributions to the right. We establish the following proposition.

Proposition 1. *There exists a productivity threshold $\bar{\varphi} > \varphi_{min}^F$ such that domestic firms with productivity $\varphi \leq \bar{\varphi}$ widen wage markdown after FDI liberalization.*

The intuition is simple. Consider an incumbent firm with $\varphi < \varphi_{min}^F$ and how many additional workers it can employ by marginally increasing wages. The marginal wage increase cannot attract workers from foreign firms and the increase leads to fewer additional employment than before. In other words, the labor supply curve to the firm

becomes less elastic. From (6), a fall in labor supply elasticity implies an expansion of wage markdown. Due to strategic complementarities, domestic firms with slightly higher productivity than φ_F also reduce wages and expand wage markdown because less productive firms reduce wages. Therefore, the threshold $\bar{\varphi}$ is larger than the productivity threshold φ_{min}^F of foreign firms.

Proposition 1 is silent about domestic firms with higher productivity than some foreign entrants. In the case of uniform distribution, we have a clear-cut result. Let $J_0(\varphi) = \varphi$ for $\varphi \in [0, 1]$ be the productivity distribution of incumbent firms and $b = 0$. FDI liberalization is an exogenous entry of foreign firms with mass N^* and with a uniform productivity distribution with support $[\varphi_{min}^F, 1]$ where $\varphi_{min}^F > 0$.

Proposition 2. *In the case of uniform distribution, there exists a threshold productivity $\bar{\varphi} \in (\varphi_{min}^F, 1)$ such that a domestic firm with productivity $\varphi > b$ widens wage markdown if $\varphi < \bar{\varphi}$ and narrows if $\varphi \geq \bar{\varphi}$.*

For productive domestic firms with $\varphi > \bar{\varphi}$, a marginal wage increase can attract workers from foreign firms as well as domestic firms. This neck-to-neck competition with foreign firms makes the labor supply curve to those firms more elastic. It therefore narrows their wage markdowns. Notice that the threshold is higher than φ_{min}^F . Thus it is possible to make a case that in terms of productivity, only the top few firms narrow their wage markdowns and the rest of firms expand them. To our knowledge, Propositions 1 and 2 are new findings in the literature.

To bring Propositions 1 and 2 to data, we investigate whether the effect of FDI liberalization on wage markdowns is heterogeneous across firms with different initial productivity. Table 9 reports the results, including interaction terms of FDI_{ct} and initial TFPR before 2002. Column (1) reports a baseline result for the sample where initial TFPR is available. Column (2) reports a result with interactions with log initial TFPR. Column (3) adds a squared log initial TFPR and its interactions. Consistent with the model's prediction, markdown widens more among firms with low initial TFPR. There is a threshold initial TFPR such that firms with higher TFPR than the threshold narrow wage markdown and firms with lower TFPR expand. Using Column

Table 9: Heterogeneous Effects of FDI Liberalization on Wage Markdowns

Log Wage Markdown	(1)	(2)	(3)
FDI Liberalization	-0.124 (0.035)	-0.260 (0.058)	-0.256 (0.061)
FDI Liberalization × log initial TFPR		0.053 (0.017)	0.073 (0.024)
FDI Liberalization × (log initial TFPR) ²			-0.006 (0.007)
Post2002 × log initial TFPR		-0.009 (0.006)	-0.033 (0.008)
Post2002 × (log initial TFPR) ²			0.008 (0.002)
Initial employment structure	X	X	X
Other policy controls	X	X	X
Vertical FDI controls	X	X	X
Firm fixed effects	X	X	X
Year fixed effects	X	X	X
Observations	531,038	531,038	531,038

Note: Standard errors are clustered at the county level in parentheses. Initial employment structure include interactions between year dummies and county's employment share of 16 sectors in 2001. Other policy controls include: (1) county's exposures to tariffs (output tariffs, input tariffs, and tariffs by foreign countries); (2) the share of state-owned enterprises among firms in a county, (3) a dummy variable indicating whether a county is a special economic zone or not. Vertical FDI controls include county's exposure to FDI liberalization in backward and forward industries.

(3), the threshold is approximately $3.72 \simeq 0.242/0.065$, which is positioned at the 81st percentile of log initial TFPR. In sum, a vast majority of low productive firms widened wage markdowns, while a few high productive firms narrowed them. On average, wage markdowns are estimated to have widened.

5 Conclusion

Recent empirical research in labor economics and industrial economics has documented that firms exercise market power in labor markets as well as in product markets.

This paper has developed an empirical framework to examine whether FDI liberalization reduces firm's monopsony power in labor markets by increasing competition. In contrast to the conventional wisdom and a fact that trade liberalization usually reduces firm's monopoly power, FDI liberalization increases firm's monopsony power on average. This finding is consistent with modern monopsony theory where the source of monopsony power is search friction rather than concentration.

Whether our finding can be applied to other countries is an open question. During our data period China's weak protection of worker's rights is common in other developing countries. An interesting question is whether better labor market institutions that reduce worker's search costs can mitigate the negative effect of FDI liberalization on monopsony power. Our estimation method of wage markdowns can be applied for typical firm-level production data in many other countries. Such international comparison is left for future research.

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Online Appendix (Not for Publication)

A1 Derivations

A1-1. Wage markdown in state-own enterprises

SOE firm's maximization problem with respect to labor is:

$$\max_{L_{jt}} R_{jt}(Y_{jt}) - w_{jt}(L_{jt})L_{jt} + \gamma L_{jt}.$$

The first order condition implies that

$$\begin{aligned} MRL_{jt} &\equiv \frac{\partial R_{jt}}{\partial L_{jt}} = w_{jt}(L_{jt}) + w'_{jt}(L_{jt})L_{jt} - \gamma \\ &= w_{jt} \left[1 + \frac{1}{\varepsilon_{jt}} - \frac{\gamma}{w_{jt}} \right] \\ &= w_{jt} \left(\frac{1 + \varepsilon_{jt}}{\varepsilon_{jt}} \right) \left[1 - \frac{\gamma}{w_{jt}} \left(\frac{\varepsilon_{jt}}{1 + \varepsilon_{jt}} \right) \right]. \end{aligned}$$

The wage markdown is then

$$\frac{w_{jt}}{MRL_{jt}} = \left(\frac{\varepsilon_{jt}}{\varepsilon_{jt} + 1} \right) \left[1 - \frac{\gamma}{w_{jt}} \left(\frac{\varepsilon_{jt}}{1 + \varepsilon_{jt}} \right) \right]^{-1}.$$

A1-2. Heterogenous Labor

Imperfectly substitutable case Suppose there are S types of workers and firm j 's production function is $Y_{jt} = Y_{jt}(L_{jt}^1, \dots, L_{jt}^S, K_{jt}, M_{jt}, \omega_{jt})$ where L_{jt}^s is type s labor input. Firm j pays wage w_{jt}^s with markdown η_{jt}^s for type s labor.

$$\eta_{jt}^s = \frac{w_{jt}^s}{\frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial Y_{jt}}{\partial L_{jt}^s}} = \left(\frac{w_{jt}^s L_{jt}^s}{P_{jt}^M M_{jt}} \right) \frac{\tilde{\theta}_{jt}^M}{\tilde{\theta}_{jt}^s} = \left(\frac{w_{jt}^s L_{jt}^s}{P_{jt}^M M_{jt}} \right) \frac{\theta_{jt}^M}{\theta_{jt}^s},$$

where $w_{jt}^s L_{jt}^s$ is the wage expenditure for type s . $\tilde{\theta}_{jt}^s \equiv \frac{\partial R_{jt}}{\partial S_{jt}} \frac{S_{jt}}{R_{jt}}$ and $\theta_{jt}^s \equiv \frac{\partial Y_{jt}}{\partial S_{jt}} \frac{S_{jt}}{Y_{jt}}$ are the revenue and output elasticities of type s labor, respectively.

In our data we can observe only total employment $L_{jt} = \sum_s L_{jt}^s$ and total wage payments $w_{jt} L_{jt} = \sum_s w_{jt}^s L_{jt}^s$. To calculate output elasticities of total employment θ_{jt}^L , we assume that a firm maintains the current skilled ratio:

$$\frac{dL_{jt}}{L_{jt}} = \frac{dL_{jt}^s}{L_{jt}^s}.$$

Then, θ_{jt}^L becomes

$$\begin{aligned} \theta_{jt}^L &= \frac{dY_{jt}}{dL_{jt}} \frac{L_{jt}}{Y_{jt}} \\ &= \left(\sum_s \frac{\partial Y_{jt}}{\partial L_{jt}^s} \frac{dL_{jt}^s}{dL_{jt}} \right) \frac{L_{jt}}{Y_{jt}} \\ &= \left(\sum_s \frac{\partial Y_{jt}}{\partial L_{jt}^s} \frac{L_{jt}^s}{L_{jt}} \right) \frac{L_{jt}}{Y_{jt}} \\ &= \sum_s \frac{\partial Y_{jt}}{\partial L_{jt}^s} \frac{L_{jt}^s}{Y_{jt}} \\ &= \sum_s \theta_{jt}^s. \end{aligned}$$

From these relationships, our markdown measure (4) becomes a weighted average of skilled wage markdown and unskilled wage markdown since

$$\begin{aligned} \eta_{jt} &= \frac{w_{jt} L_{jt}}{P_{jt}^M M_{jt}} \frac{\theta_{jt}^M}{\theta_{jt}^s} \\ &= \frac{\theta_{jt}^M}{P_{jt}^M M_{jt}} \left(\frac{\sum_s w_{jt}^s L_{jt}^s}{\sum_s \theta_{jt}^s} \right) \\ &= \sum_s \left(\frac{\theta_{jt}^s}{\sum_s \theta_{jt}^s} \right) \left(\frac{w_{jt}^s L_{jt}^s}{P_{jt}^M M_{jt}} \right) \frac{\theta_{jt}^M}{\theta_{jt}^s} \\ &= \sum_s \left(\frac{\theta_{jt}^s}{\sum_s \theta_{jt}^s} \right) \eta_{jt}^s. \end{aligned} \tag{14}$$

Perfectly substitutable case An interesting special case is when skill types are perfectly substitutable. The production function includes labor L_{jt}^* in an efficiency unit:

$$Y_{jt} = Y_{jt}(L_{jt}^*, K_{jt}, M_{jt}, \omega_{jt}) \text{ and } L_{jt}^* = \sum_s \nu_{jt}^s L_{jt}^s$$

where L_{jt}^s is the amount of type s labor and ν_{jt}^s is a skill converter that can vary across firms and time. Let w_{jt}^* be the wage for an efficiency unit. Perfect substitutability then implies that

$$w_{jt}^s = \nu_{jt}^s w_{jt}^* \text{ and } \frac{\partial Y_{jt}}{\partial L_{jt}^s} = \nu_{jt}^s \frac{\partial Y_{jt}}{\partial L_{jt}^*}.$$

Therefore, wage markdown against type s labor becomes

$$\eta_{jt}^s \equiv \frac{w_{jt}^s}{\frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial Y_{jt}}{\partial L_{jt}^s}} = \frac{\nu_{jt}^s w_{jt}^*}{\nu_{jt}^s \frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial Y_{jt}}{\partial L_{jt}^*}} = \frac{w_{jt}^*}{\frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial Y_{jt}}{\partial L_{jt}^*}} \equiv \eta_{jt}^*.$$

Then, from equation (14), our markdown measure η_{jt} equals to this common markdown η_{jt}^* .

A1.3 Labor share decomposition

Using the first order condition for profit maximization $\frac{\partial R_{jt}}{\partial Y_{jt}} = mc_{jt}$, MRL can be simplified as

$$\begin{aligned} MRL_{jt} &= \frac{\partial R_{jt}}{\partial Y_{jt}} \frac{\partial F_{jt}}{\partial L_{jt}} \\ &= mc_{jt} \frac{\partial F_{jt}}{\partial L_{jt}} \\ &= \frac{mc_{jt}}{P_{jt}} \left(\frac{\partial F_{jt}}{\partial L_{jt}} \frac{L_{jt}}{F_{jt}} \right) \frac{P_{jt} Y_{jt}}{L_{jt}} \\ &= \frac{\theta_{jt}^L}{\mu_{jt}} \left(\frac{P_{jt} Y_{jt}}{L_{jt}} \right) \end{aligned}$$

The labor income share in value-added then becomes

$$\begin{aligned}\frac{w_{jt}L_{jt}}{VA_{jt}} &= \eta_{jt}L_{jt} \left(\frac{MRL_{jt}}{VA_{jt}} \right) \\ &= \frac{\eta_{jt}\theta_{jt}^L}{\mu_{jt}} \left(\frac{P_{jt}Y_{jt}}{VA_{jt}} \right).\end{aligned}$$

A2 FDI liberalization in canonical monopsony models

A2.1 Employer concentration

The concentration of employers (e.g. company towns) is a classic reason that firms face upward sloping labor supply curves. Consider Cournot oligopsony as a canonical model. There are N firms and each firm j decides employment L_j , taking other firm's employment as given. Let L^A be the aggregate employment and $w(L^A)$ be an inverse labor supply curve to the industry with elasticity $\varepsilon^A \equiv \frac{w(L^A)}{w'(L^A)L^A} > 0$. Let $R(\varphi_j, L_j)$, φ_j , L_j and $s_j \equiv L_j/L^A$ be firm j 's revenue, productivity, employment and employment share, respectively. Firm j 's profit maximization problem can then be written as

$$\max_{L_j} R(\varphi_j, L_j) - w \left(\sum_j L_j \right) L_j$$

The first order condition leads to wage markdowns

$$\eta_j = \frac{\varepsilon_j}{\varepsilon_j + 1} = \frac{\varepsilon^A/s_j}{\varepsilon^A/s_j + 1}. \quad (15)$$

Thus, the elasticity of labor supply to an individual firm $\varepsilon_j = \varepsilon^A/s_j$ depends on industry-level labor supply and the firm's employment share.

Cournot oligopsony conforms with the conventional wisdom. First, equation (15) implies that when we compare two firms j and k , $\eta_j > \eta_k$ if and only if $s_j < s_k$. Thus, large employers exercise greater monopsony power and exhibit wider markdowns than small employers. In a typical case where $\partial^2 R/\partial\varphi\partial L > 0$, employment increases in

productivity. Thus, monopsony power increases in productivity. Second, equation (15) implies a limit theorem for Cournot oligopsony. When the number of firms increases toward infinity and ε^A is finite, each firm's employment share approaches zero and markdowns converge to one as in a perfectly competitive labor market. This limit theorem contributes to the conventional wisdom that new entrants such as those after FDI liberalization reduce incumbent firm's monopsonic power and narrows their wage markdowns.¹⁶

A2.2. Job Differentiation

In a goods market, a firm may face a downward-sloping demand curve because of product differentiation. Similarly, a firm may face an upward-sloping labor supply curve because of job differentiation. That is, workers may have preferences for jobs' non-monetary characteristics so that a wage cut does not necessarily lead to losing all of the employees. As a canonical model, we consider a logit model (e.g., Card, Cardoso, Heining and Klein, 2018). There are N firms that produce a homogenous numeraire good from labor and constant returns to scale technology. A worker n receives net utility $U_{nj} = \ln v_j(w_j) + \varepsilon_{nj}$ from working at firm j , where w_j is firm j 's wage. The second term ε_{nj} is the worker's utility from non-monetary characteristics of working at firm j , and it independently follows the Gumbel distribution. There is a continuum of workers with mass L , and workers are homogenous except ε_{nj} . By standard arguments (McFadden, 1973), a labor supply supply curve to firm j becomes

$$L_j(w_j) = \left(\frac{v_j(w_j)}{\sum_{k=1}^N v_k(w_k)} \right) L^A, \quad (16)$$

where N is the number of firms and L^A is the aggregate labor supply. Let $R(\varphi_i, L_i)$, φ_i , L_i and $s_j \equiv L_j/L^A$ be firm j 's revenue, productivity, employment and employment

¹⁶Of course, if new entry is finite, it is theoretically possible that markdowns expands, i.e. ε^A/s_j decreases, when ε^A shrinks significantly and offsets a fall in employment shares s_j . However, this is not considered as a typical case.

share, respectively. Firm j 's profit maximization problem is written as

$$\max_{w_j} R(\varphi_j, L_j(w_j)) - w_j L_j(w_j) \text{ subject to (16).}$$

In a typical case where $\partial^2 R / \partial \varphi \partial L > 0$, wage is increasing in productivity. Thus, more productive firms offer higher wages to hire more workers. Since the elasticity of labor supply is $\varepsilon_j = \kappa_j(w_j)(1 - s_j)$, wage markdown is

$$\eta_j = \frac{\varepsilon_j}{\varepsilon_j + 1} = \frac{\kappa_j(w_j)(1 - s_j)}{\kappa_j(w_j)(1 - s_j) + 1}, \quad (17)$$

where $\kappa_j(w) \equiv v'_j(w_j)w_j/v(w_j)$ is the elasticity of v_j and $s_j \equiv L_j/L^A$ is firm j 's employment share.

In the logit oligopsony model, wage markdown is determined by the curvature of monetary utility as well as by concentration. When $\kappa_j = \kappa$ for all j , the logit model predicts similar results to Cournot oligopsony. First, equation (6) implies that when we compare two firms j and k , $\eta_j > \eta_k$ if and only if $s_j < s_k$. Larger and more productive employers exercise greater monopsony power and exhibit wider markdowns than smaller and lower productive employers. FDI liberalization will shrink the wage markdowns of incumbents by decreasing their employment shares. When $\kappa_j(w_j)$ can vary with the wage, these predictions become ambiguous. When N is large and the market becomes monopsonically competitive, $\varepsilon_j = \kappa_j(w_j)$ holds and wage markdowns are determined solely by the curvature of the monetary utility κ_j . Therefore, it is theoretically possible that FDI liberalization widens wage markdowns of incumbents.

A2.3 An equilibrium of the Burdett-Mortensen model

This section presents calculations for obtaining an equilibrium in the Burdett-Mortensen model which are omitted from the main text.

Labor supply curve A stationary steady state requires the size of unemployed workers and that of each wage group to be stable overtime, which implies the following two

conditions:

$$\begin{aligned} \delta(1-u)L &= \lambda uL, \\ \lambda F(w)uL &= [\delta + \lambda(1-F(w))] N \int_b^w l(t) dF(t) \text{ for all } w \text{ on the support of } F(w), \end{aligned} \tag{18}$$

where u is unemployment rate, N is the number of firms in this labor market, $l(w)$ is the employment in a firm that offers wage w , and $F(w)$ is the distribution of wage offers among firms. The first equation represents the size of unemployed workers. The inflow into unemployment on the left-hand side equals the outflow from unemployment on the right-hand side. The second equation is the inflow and the outflow into a group of employed workers who currently receive wages lower than w . The left-hand side expresses that a mass uL of unemployed workers join this group with probability $\lambda F(w)$. The right-hand side expresses that workers in this group with size $N \int_b^w l(t) dF(t)$ leave the group either because of being unemployed with rate δ or moving to better-paying job with rate $\lambda(1-F(w))$.

A celebrated result by Burdett and Mortensen (1998) is that F has a continuous support $[b, \bar{w}]$ for some $\bar{w} > b$. See their paper for a formal proof. The intuition is that if the support is $[b, w_0] \cup [w_1, \bar{w}]$ and $w_1 > w_0$ with a gap, a firm setting w_0 can disproportionately increase employment and profits by infinitesimally increasing its wage to $w_0 + \varepsilon$. Differentiating (18) by w , we obtain a positive relation between employment and wage in a steady state:

$$l(w) = \frac{Lk}{N[1+k(1-F(w))]^2} \text{ for } w \in [b, \bar{w}], \tag{19}$$

where $k \equiv \lambda/\delta$.

Equilibrium wage markdown We obtain an equilibrium as follows. Substituting $F(w(\varphi)) = J(\varphi)$ into the labor supply curve, we obtain equilibrium employment of

firm with productivity φ :

$$L(\varphi) = l(w(\varphi)) = \frac{Lk}{N[1 + k(1 - J(\varphi))]^2}. \quad (20)$$

By applying the envelop theorem for $\pi(\varphi)$ in (13), we obtain $\pi'(\varphi) = L(\varphi)$. Integrating and setting $\pi(b) = 0$ yields the profit function

$$\begin{aligned} \pi(\varphi) &= \int_b^\varphi \pi'(x) dx + \pi(b) \\ &= \int_b^\varphi L(x) dx \\ &= (\varphi - b)\bar{L}(\varphi) \end{aligned}$$

where

$$\bar{L}(\varphi) \equiv \frac{1}{\varphi - b} \int_b^\varphi l(s) ds \quad (21)$$

may be interpreted as a weighted average of employment among firms with productivity lower than φ . From the above, we obtain

$$\pi(\varphi) = (\varphi - w(\varphi))L(\varphi) = (\varphi - b)\bar{L}(\varphi).$$

Then, we obtain the markdown $\eta(\varphi) \equiv w(\varphi)/\varphi$ as

$$\begin{aligned} \eta(\varphi) &= \frac{w(\varphi)}{\varphi} \\ &= 1 - \left(\frac{\varphi - b}{\varphi}\right) \frac{\bar{L}(\varphi)}{L(\varphi)} \\ &= 1 - \frac{1}{\varphi} \int_b^\varphi \left(\frac{1 + k(1 - J(\varphi))}{1 + k(1 - J(s))}\right)^2 ds \\ &= 1 - \frac{\int_b^\varphi f(s) ds}{f(\varphi)\varphi} \end{aligned} \quad (22)$$

where

$$f(\varphi) \equiv \left(\frac{1}{1 + k(1 - J(s))}\right)^2.$$

Uniform distribution case Define

$$\vartheta(\varphi) \equiv \frac{1}{\varphi} \int_0^\varphi \left(\frac{1+k(1-J(\varphi))}{1+k(1-J(s))} \right)^2 ds \text{ and } v \equiv \frac{k}{1+k}.$$

Then, it follows that

$$\begin{aligned} \vartheta(\varphi) &= \frac{1}{\varphi} \int_0^\varphi \left(\frac{1+k(1-s)}{1+k(1-s)} \right)^2 ds \\ &= \frac{(v-\varphi)^2}{\varphi} \int_0^\varphi \frac{1}{(v-s)^2} ds \\ &= \frac{(v-\varphi)^2}{\varphi} \int_0^\varphi \left(\frac{1}{v-s} \right)' ds. \\ &= \frac{(v-\varphi)^2}{\varphi} \left[\frac{1}{v-\varphi} - \frac{1}{v} \right] \\ &= \frac{(v-\varphi)^2}{\varphi} \left[\frac{\varphi}{v(v-\varphi)} \right] \\ &= \frac{v-\varphi}{v}. \end{aligned}$$

We obtain the markdown function

$$\eta(\varphi) = 1 - \vartheta(\varphi) = \frac{\varphi}{v} = \frac{k}{1+k} \varphi.$$

Proof for Proposition 1 Define

$$a(s) \equiv \frac{f_0(s)}{f_1(s)} = \left(\frac{1-\rho J_1(s)}{1-\rho J_0(s)} \right)^2$$

where $\rho \equiv k/(1+k)$. We first prove the following lemmas.

Lemma 1. *If $a'(s) \geq 0$ for all $s \leq \varphi$, then $\eta_1(\varphi) < \eta_0(\varphi)$.*

Proof. Under the condition, it holds that

$$\frac{\int_b^\varphi f_0(s) ds}{f_0(\varphi)} = \frac{\int_b^\varphi a(s) f_1(s) ds}{a(\varphi) f_1(\varphi)} < \frac{a(\varphi) \int_b^\varphi f_1(s) ds}{a(\varphi) f_1(\varphi)} = \frac{\int_b^\varphi f_1(s) ds}{f_1(\varphi)}.$$

Thus, $\eta_1(\varphi) < \eta_0(\varphi)$ from (22). \square

Lemma 2. *If φ is lower than productivities of all foreign entrants, then $a'(s) \geq 0$ for all $s \in (b, \varphi]$.*

Proof. Under the condition, the share of low productive firms decreases: $j_0(s) > j_1(s)$ and $J_0(s) > J_1(s)$ for all $s \leq \varphi$. Then,

$$\begin{aligned} a'(s) &= 2a(s)^{1/2} \left[\frac{-\rho j_1(s)(1 - \rho J_0(s)) + \rho j_0(s)(1 - \rho J_1(s))}{(1 - \rho J_0(s))^2} \right] \\ &= 2a(s)^{1/2} \left[\frac{\rho(j_0(s) - j_1(s))(1 - \rho J_1(s)) + \rho^2 j_1(s)(J_0(s) - J_1(s))}{(1 - \rho J_0(s))^2} \right] > 0. \end{aligned} \quad (23)$$

\square

Proof for Proposition 2

Proof. Let $N_0 = N$ and $N_1 = N + N^*$ be the mass of firms before and after liberalization. In the uniform case, $J_0(s) = s$ and

$$J_1(s) = \begin{cases} \beta s & \text{for } \varphi \in [0, \varphi_{min}^F] \\ 1 - \theta(1 - s) & \text{for } \varphi \in [\varphi_{min}^F, 1], \end{cases}$$

where $\beta = \frac{N_0}{N_1} < 1$ and $\theta \equiv (1 - a\beta)/(1 - a) > 1$. Then, their densities become $j_0(s) = 1$ and

$$j_1(s) = \begin{cases} \beta & \text{for } \varphi \in [0, \varphi_{min}^F] \\ \theta & \text{for } \varphi \in [\varphi_{min}^F, 1]. \end{cases}$$

From (23),

$$a'(\varphi) = \begin{cases} 2a(s)^{1/2} \left[\frac{\rho(1-\beta)}{(1-\rho s)^2} \right] > 0 & \text{for } \varphi \in (0, \varphi_{min}^F) \\ -2a(s)^{1/2} \left[\frac{\rho(\theta-1)(1-\rho)}{(1-\rho s)^2} \right] < 0 & \text{for } \varphi \in (\varphi_{min}^F, 1). \end{cases}$$

Since $a(0) = a(1) = 1$ and $a(s)$ is continuous, it holds that $a(s) > 1$ for $s \in (0, 1)$. Therefore, we have $\eta_0(1) < \eta_1(1)$ since

$$\frac{\int_b^1 f_0(s)ds}{f_0(1)} = \frac{\int_b^1 a(s)f_1(s)ds}{a(1)f_1(1)} > \frac{a(1) \int_b^1 f_1(s)ds}{a(1)f_1(1)} = \frac{\int_b^1 f_1(s)ds}{f_1(\varphi)}.$$

From Proposition 1, $\eta_0(\varphi_{min}^F) > \eta_1(\varphi_{min}^F)$. Since $\frac{\int_b^{\varphi} f_0(s)ds}{f_0(\varphi)}$ and $\frac{\int_b^{\varphi} f_1(s)ds}{f_1(\varphi)}$ are continuous, there exists a threshold $\bar{\varphi}$ such that

$$\frac{\int_b^{\bar{\varphi}} f_0(s)ds}{f_0(\bar{\varphi})} = \frac{\int_b^{\bar{\varphi}} f_1(s)ds}{f_1(\bar{\varphi})}.$$

□

A3 Production Function Estimation

Consider the following production function of firm j at time t in the level and log forms, respectively:

$$Y_{jt} = F(k_{jt}, l_{jt}, m_{jt}) \exp(\omega_{jt} + \varepsilon_{jt})$$

$$y_{jt} = f(k_{jt}, l_{jt}, m_{jt}) + \omega_{jt} + \varepsilon_{jt},$$

where $y_{jt} \equiv \ln Y_{jt}$, $k_{jt} \equiv \ln K_{jt}$, $l_{jt} \equiv \ln L_{jt}$, and $m_{jt} \equiv \ln M_{jt}$. Function $f \equiv \ln F$ takes a flexible form and will be approximated by polynomials below. Terms ω_{jt} and ε_{jt} are Hicks neutral productivity shocks: ε_{jt} is unanticipated to production and i.i.d. shocks with $E[\varepsilon_{jt}] = 0$ including measurement errors; ω_{jt} are known to firms when materials m_{jt} and labor l_{jt} are chosen, but unknown when capital k_{jt} (or investment at $t - 1$) is chosen. In the estimation, f is assumed to be common throughout the 2-digit industry-level.

Following De Loecker (2011) and GNR, the output market is assumed to be monopolistically competitive in each 4 digit product market. Each firm faces an individual

demand curve derived from the CES utility function:

$$Y_{jt} = Y_{gt} \left(\frac{P_{jt}}{\Pi_{gt} \exp(\chi_{jt})} \right)^{\sigma_{st}} \quad \text{where } \sigma_t < -1, \quad (24)$$

P_{jt} is firm j 's price, Π_{gt} is the product-level (4-digit industry level) price index, Y_{gt} is product-level demand-shifter and χ_{jt} is a firm-level demand shifter that is known to the firm. Following De Loecker (2011) and GNR, the elasticity of demand $\sigma_{st} (< -1)$ is defined as negative, is specific to a subgroup s of firms, and may vary over time. This implies that an expected output markup is also subgroup-time specific, though realized markups can vary across firms within subgroups. A subgroup s is obtained by dividing each 3-digit category into two groups of 4-digit products based on whether or not they are classified as FDI-liberalized products.¹⁷

From the demand function (24), firm's revenue $R_{jt} = P_{jt}Y_{jt}$ becomes

$$R_{jt} = Y_{gt}^{-1/\sigma_{st}} \Pi_t \exp(\tilde{\varepsilon}_{jt} + \omega_{jt}^\mu) [F(k_{jt}, l_{jt}, m_{jt})]^{(\sigma_{st}+1)/\sigma_{st}}, \quad (25)$$

where $\omega_{jt}^\mu \equiv \chi_{jt} + \left(\frac{\sigma_{st}+1}{\sigma_{st}} \right) \omega_{jt}$ is a combined positive shock to firm revenue known to the firm at time t . Following De Loecker (2011; 2013), we assume that ω_{jt}^μ follow a Markov process $\omega_{jt}^\mu = h(\omega_{jt-1}^\mu, \mathbf{W}_{jt-1}) + \eta_{jt}^\mu$ where firms with different characteristics \mathbf{W}_{jt-1} face different productivity motions, which will be specified below.

Consider the expected profit maximization with respect to materials,

$$\max_{M_{jt}} Y_{gt}^{-1/\sigma_{st}} \Pi_t \exp(\omega_{jt}^\mu) [F(k_{jt}, l_{jt}, m_{jt})]^{(\sigma_{st}+1)/\sigma_{st}} \tilde{\mathcal{E}} - P_{jt}^M M_{jt}$$

where $\tilde{\mathcal{E}} \equiv E[\exp(\tilde{\varepsilon}_{jt})]$ and $\tilde{\varepsilon}_{jt} \equiv \left(\frac{\sigma_{st}+1}{\sigma_{st}} \right) \varepsilon_{jt}$. Using (25), we obtain the first order condition as:

$$\left(\frac{\sigma_{st} + 1}{\sigma_{st}} \right) \exp(-\tilde{\varepsilon}_{jt}) \frac{R_{jt}}{F} \frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{\partial M_{jt}} \tilde{\mathcal{E}} = P_{jt}^M$$

¹⁷Theoretically one could allow σ_{gt} to be product-time varying, but the sample becomes too small to obtain stable coefficients.

By taking the log of both sides, using $\frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}} = \frac{M_{jt}}{F} \frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{\partial M_{jt}}$, and denoting $s_{jt} \equiv \ln \alpha_{jt}^M = \ln \left(\frac{P_{jt}^M M_{jt}}{R_{jt}} \right)$, the first order condition is simplified to

$$s_{jt} = \ln \left(\frac{\sigma_{st} + 1}{\sigma_{st}} \right) + \ln \tilde{\mathcal{E}} + \ln \frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}} - \tilde{\varepsilon}_{jt}.$$

We approximate output elasticities on materials, $\frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}} = \exp(\mu) D^\mu(k_{jt}, l_{jt}, m_{jt}; \gamma)$ where μ is constant to be estimated below and $D^\mu(k_{jt}, l_{jt}, m_{jt}; \gamma)$ is a second order polynomials

$$\begin{aligned} D^\mu(k_{jt}, l_{jt}, m_{jt}; \gamma) \equiv & \gamma_0 + \gamma_k k_{jt} + \gamma_l l_{jt} + \gamma_m m_{jt} + \gamma_{kk} k_{jt}^2 + \gamma_{ll} l_{jt}^2 \\ & + \gamma_{mm} m_{jt}^2 + \gamma_{kl} k_{jt} l_{jt} + \gamma_{km} k_{jt} m_{jt} + \gamma_{lm} l_{jt} m_{jt}, \end{aligned}$$

where $\gamma \equiv (\gamma_0, \gamma_k, \gamma_l, \gamma_m, \gamma_{kk}, \gamma_{ll}, \gamma_{mm}, \gamma_{kl}, \gamma_{km}, \gamma_{lm})$ is a vector of parameters.

The estimation consists of two steps. The first step is to estimate

$$\begin{aligned} s_{jt} &= \left[\ln \left(\frac{\sigma_{st} + 1}{\sigma_{st}} \right) + \mu + \ln \tilde{\mathcal{E}} \right] + \ln D^\mu(k_{jt}, l_{jt}, m_{jt}; \gamma) - \tilde{\varepsilon}_{jt} \\ &= \delta_{st} + \ln D^\mu(k_{jt}, l_{jt}, m_{jt}; \gamma) - \tilde{\varepsilon}_{jt} \end{aligned} \quad (26)$$

by non-linear least squares where δ_{st} is subgroup-year fixed effects and $\tilde{\varepsilon}_{jt}$ is treated as an error term. Using the residuals $\hat{\tilde{\varepsilon}}_{jt}$, we construct $\hat{\tilde{\mathcal{E}}}$, an estimate of $\tilde{\mathcal{E}} \equiv E[\exp(\tilde{\varepsilon}_{jt})]$, by the sample mean of $\exp(\hat{\tilde{\varepsilon}}_{jt})$.

Consider the log of the real revenue function deflated by the price index $r_{jt} \equiv \ln(R_{jt}/\Pi_t)$ from (25):

$$r_{jt} = \left(\frac{\sigma_{st} + 1}{\sigma_{st}} \right) f(k_{jt}, l_{jt}, m_{jt}) - \frac{1}{\sigma_{st}} \ln Y_{gt} + \omega_{jt}^\mu + \tilde{\varepsilon}_{jt}. \quad (27)$$

Substituting $\left(\frac{\sigma_{st}+1}{\sigma_{st}}\right) = \exp\left(\hat{\delta}_{st} - \mu\right) / \hat{\mathcal{E}}$, we obtain

$$r_{jt} = \frac{\exp\left(\hat{\delta}_{st}\right)}{\hat{\mathcal{E}}} \exp(-\mu) f(k_{jt}, l_{jt}, m_{jt}) - \left[\frac{\exp\left(\hat{\delta}_{st} - \mu\right)}{\hat{\mathcal{E}}} - 1 \right] \ln Y_{gt} + \omega_{jt}^{\mu} + \tilde{\varepsilon}_{jt}. \quad (28)$$

Following Klette and Griliches (1996), De Loecker (2010) and GNR, we use the market share weighted average of deflated revenues $\ln \hat{Y}_{gt} \equiv \sum_{j=1}^N \left(R_{jt} / \sum_{k \in N_{gt}} R_{kt} \right) r_{jt}$ for the product demand shifter $\ln Y_{gt}$, where N_{gt} is the set of firms that produce positive output of product g in both t and $t-1$. Since $D^{\mu}(k_{jt}, l_{jt}, m_{jt}; \gamma) = \exp(-\mu) \frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}}$, its integration by m_{jt} leads to

$$\exp(-\mu) f(k_{jt}, l_{jt}, m_{jt}) = \int D^{\mu}(k_{jt}, l_{jt}, m_{jt}; \gamma) dm_{jt} + \exp(-\mu) \mathcal{C}(k_{jt}, l_{jt}), \quad (29)$$

where $\mathcal{C}(k_{jt}, l_{jt}) \equiv f(k_{jt}, l_{jt}, m_{jt}) - \int \frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}} dm_{jt}$ is the constant of the integration that is a function of k_{jt} and l_{jt} . We approximate $\mathcal{C}(k_{jt}, l_{jt})$ with second order polynomials in k_{jt} and l_{jt} :¹⁸

$$\mathcal{C}(k_{jt}, l_{jt}, \kappa) \equiv \kappa_k k_{jt} + \kappa_l l_{jt} + \kappa_{kk} k_{jt}^2 + \kappa_{ll} l_{jt}^2 + \kappa_{kl} k_{jt} l_{jt},$$

where $\kappa \equiv (\kappa_k, \kappa_l, \kappa_{kk}, \kappa_{ll}, \kappa_{kl})$ is a vector of parameters.

Using the estimated coefficients $\hat{\gamma}$, $\hat{\delta}_{st}$, residuals, $\hat{\mathcal{E}}$ from (26) and real revenue r_{jt} , we can construct

$$\mathcal{R}_{jt} \equiv r_{jt} - \frac{\exp\left(\hat{\delta}_{st}\right)}{\hat{\mathcal{E}}} \int D^{\mu}(k_{jt}, l_{jt}, m_{jt}; \hat{\gamma}) dm_{jt} - \hat{\varepsilon}_{jt}$$

¹⁸Note that $\mathcal{C}(k_{jt}, l_{jt})$ should not include a constant term because $f(k_{jt}, l_{jt}, m_{jt})$ does not contain it.

where

$$\int D^\mu(k_{jt}, l_{jt}, m_{jt}; \hat{\gamma}) dm_{jt} = m_{jt} \left(\hat{\gamma}_0 + \hat{\gamma}_k k_{jt} + \hat{\gamma}_l l_{jt} + \frac{\hat{\gamma}_m}{2} m_{jt} + \hat{\gamma}_{kk} k_{jt}^2 + \hat{\gamma}_{ll} l_{jt}^2 + \frac{\hat{\gamma}_{mm}}{3} m_{jt}^2 + \hat{\gamma}_{kl} k_{jt} l_{jt} + \frac{\hat{\gamma}_{km}}{2} k_{jt} m_{jt} + \frac{\hat{\gamma}_{lm}}{2} l_{jt} m_{jt} \right).$$

Substituting \mathcal{R}_{jt} and (29) into (28), we obtain ω_{jt}^μ from (28) as a function of μ and κ :

$$\omega_{jt}^\mu = \mathcal{R}_{jt} - \frac{\exp(\hat{\delta}_{st} - \mu)}{\hat{\mathcal{E}}} \mathcal{C}(k_{jt}, l_{jt}, \kappa) + \frac{\exp(\hat{\delta}_{st} - \mu)}{\hat{\mathcal{E}}} \ln \hat{Y}_{gt}.$$

Letting $\rho \equiv \left[\hat{\mathcal{E}} \exp(\mu) \right]^{-1}$ and $v \equiv \rho \kappa$ further simplifies ω_{jt}^μ as a function of ρ and v :

$$\omega_{jt}^\mu(\rho, v) = \tilde{\mathcal{R}}_{jt} - \tilde{\mathcal{C}}(k_{jt}, l_{jt}, v) + \rho \ln \tilde{Y}_{gt}$$

where $\tilde{\mathcal{R}}_{jt} \equiv \mathcal{R}_{jt} - \ln \hat{Y}_{gt}$, $\ln \tilde{Y}_{gt} \equiv \exp(\hat{\delta}_{st}) \ln \hat{Y}_{gt}$ and $\tilde{\mathcal{C}}(k_{jt}, l_{jt}, v) \equiv \exp(\hat{\delta}_{st}) \mathcal{C}(k_{jt}, l_{jt}, v)$.

The dynamic motion of ω_{jt}^μ can be written as

$$\omega_{jt}^\mu(\rho, \zeta) = h(\omega_{jt-1}^\mu(\rho, v), \mathbf{W}_{jt-1}, \delta_p, \delta_g) + \xi_{jt}.$$

The control variables \mathbf{W}_{jt} include the following variables on ownerships, trade and FDI that potentially affect productivity evolution: a dummy indicating the state-owned enterprises (SOEs dummy), a dummy indicating the foreign-invested enterprises (FIEs dummy), an export status dummy, output tariffs, input tariffs constructed from an input-output table, FDI equity shares in the industry (horizontal FDI), FDI equity shares in the upstream industries (backward FDI), FDI equity shares in the downstream industries (forward FDI). δ_p and δ_g are province fixed effects and four-digit industry

fixed effects, respectively. We approximate h with the second order polynomials

$$h(\omega_{jt-1}^\mu, \mathbf{W}_{jt-1}, \delta_p, \delta_g) = \delta_p + \delta_g + \zeta_\omega \omega_{jt-1}^\mu + \zeta_{\omega\omega} (\omega_{jt-1}^\mu)^2 + \mathbf{W}'_{jt-1} \boldsymbol{\zeta}_W \\ + \omega_{jt-1}^h \mathbf{W}'_{jt-1} \boldsymbol{\zeta}_{\omega W} + (\omega_{jt-1}^h)^2 \mathbf{W}'_{jt-1} \boldsymbol{\zeta}_{\omega\omega z}.$$

We estimate the parameters as follows. We first choose a given value of (ρ, v) and regress $\omega_{jt}^\mu(\rho, v)$ on $h(\omega_{jt-1}^\mu(\rho, v), \mathbf{W}_{jt-1}, \delta_p, \delta_g)$ to obtain $\xi_{jt}(\rho, v)$ as a function of (ρ, v) . Following De Loecker (2011) and De Loecker and Warzynski (2012), we assume

$$\mathbf{M}_{jt} \equiv \left(k_{jt}, l_{jt-1}, k_{jt}^2, l_{jt-1}^2, k_{jt}l_{jt-1}, \ln \hat{Y}_{t-1} \right)'$$

are pre-determined at time t and orthogonal to the productivity innovation $\xi_{jt}(\rho, v)$. Then, we construct six moment conditions $E(\xi_{jt}(\rho, v)\mathbf{M}_{jt}) = 0$ and estimate six parameters (ρ, v) by GMM.¹⁹

Once we obtain $(\hat{\rho}, \hat{v})$, we first obtain $\exp(\hat{\mu}) = [\hat{\mathcal{E}}\hat{\rho}]^{-1}$ and $\hat{\kappa} = \hat{v} \left[\exp(\hat{\delta}_{st}) \hat{\rho} \right]^{-1}$. Then, we obtain output elasticities $\hat{\theta}_{jt}^L$ and $\hat{\theta}_{jt}^M$. First, material elasticities are obtained from $\hat{\theta}_{jt}^M = \frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}} = \exp(\hat{\mu}) D^\mu(k_{jt}, l_{jt}, m_{jt}; \hat{\gamma})$. Defining $\tilde{\gamma}_i \equiv \hat{\gamma}_i \exp(\hat{\mu})$, we obtain

$$\hat{\theta}_{jt}^M = \exp(\hat{\mu}) \left(\hat{\gamma}_0 + \hat{\gamma}_k k_{jt} + \hat{\gamma}_l l_{jt} + \hat{\gamma}_m m_{jt} + \hat{\gamma}_{kk} k_{jt}^2 + \hat{\gamma}_{ll} l_{jt}^2 \right. \\ \left. + \hat{\gamma}_{mm} m_{jt}^2 + \hat{\gamma}_{kl} k_{jt} l_{jt} + \hat{\gamma}_{km} k_{jt} m_{jt} + \hat{\gamma}_{lm} l_{jt} m_{jt} \right).$$

¹⁹For ρ to satisfy $\rho \in (0, 1)$, we transform $\varsigma \equiv \ln\left(\frac{1-\rho}{\rho}\right)$, estimate ς and obtain $\hat{\rho} = 1/(1 + \exp(\hat{\varsigma}))$. We pick the initial value of (ρ_0, v_0) as follows. We try 9 different initial values for ρ_0 $\{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$ and choose a case where the objective function is minimized. For a given ρ_0 , we obtain a vector of initial values v_0 as follows. We regress the OLS regression of r_j on the second order polynomials of (k_{jt}, l_{jt}) and $\ln \hat{Y}_t$ with controls \mathbf{W}_{jt-1} , province fixed effects, and four-digit industry fixed effects. Then, we multiply estimated coefficients of $\{k, l, k^2, l^2, kl\}$ by ρ_0 to obtain v_0 , following (27).

The estimated production function is then

$$\begin{aligned}
\hat{f}(k_{jt}, l_{jt}, m_{jt}) &= \exp(\hat{\mu}) \int D^\mu(k_{jt}, l_{jt}, m_{jt}; \hat{\gamma}) dm_{jt} + \mathcal{E}(k_{jt}, l_{jt}, \hat{\kappa}), \\
&= \exp(\hat{\mu}) m_{jt} \left(\hat{\gamma}_0 + \hat{\gamma}_k k_{jt} + \hat{\gamma}_l l_{jt} + \frac{\hat{\gamma}_m}{2} m_{jt} + \hat{\gamma}_{kk} k_{jt}^2 + \hat{\gamma}_{ll} l_{jt}^2 \right. \\
&\quad \left. + \frac{\hat{\gamma}_{mm}}{3} m_{jt}^2 + \hat{\gamma}_{kl} k_{jt} l_{jt} + \frac{\hat{\gamma}_{km}}{2} k_{jt} m_{jt} + \frac{\hat{\gamma}_{lm}}{2} l_{jt} m_{jt} \right) \\
&\quad + \hat{\kappa}_k k_{jt} + \hat{\kappa}_l l_{jt} + \hat{\kappa}_{kk} k_{jt}^2 + \hat{\kappa}_{ll} l_{jt}^2 + \hat{\kappa}_{kl} k_{jt} l_{jt}.
\end{aligned}$$

Thus, the labor elasticities $\hat{\theta}_{jt}^L = \frac{\partial \hat{f}(k_{jt}, l_{jt}, m_{jt})}{\partial l_{jt}}$ are obtained as

$$\hat{\theta}_{jt}^L = \exp(\hat{\mu}) m_{jt} \left(\hat{\gamma}_l + 2\hat{\gamma}_{ll} l_{jt} + \hat{\gamma}_{kl} k_{jt} + \frac{\hat{\gamma}_{lm}}{2} m_{jt} \right) + \hat{\kappa}_l + 2\hat{\kappa}_{ll} l_{jt} + \hat{\kappa}_{kl} k_{jt}.$$

Similarly, the capital elasticities $\hat{\theta}_{jt}^K = \frac{\partial \hat{f}(k_{jt}, l_{jt}, m_{jt})}{\partial k_{jt}}$ are obtained as

$$\hat{\theta}_{jt}^K = \exp(\hat{\mu}) m_{jt} \left(\hat{\gamma}_k + 2\hat{\gamma}_{kk} k_{jt} + \hat{\gamma}_{kl} l_{jt} + \frac{\hat{\gamma}_{km}}{2} m_{jt} \right) + \hat{\kappa}_k + 2\hat{\kappa}_{kk} k_{jt} + \hat{\kappa}_{kl} l_{jt}.$$

Once the production function coefficients have been estimated, we can calculate output elasticities $\hat{\theta}_{jt}^L$ and $\hat{\theta}_{jt}^M$ and estimate wage markdowns by (4). The revenue elasticities are obtained by multiplying $\exp(\hat{\delta}_{st}) \hat{\rho}$ by the output elasticities.

We obtain TFPR as the residual of revenue from inputs, which contains TFP and industry-level and firm-level demand shifters:

$$\begin{aligned}
\ln TFPR_{jt} &\equiv -\frac{1}{\sigma_{st}} \ln Y_{jt} + \chi_{jt} + \left(\frac{\sigma_{st} + 1}{\sigma_{st}} \right) \omega_{jt}. \\
&= r_{jt} - \left(\frac{\sigma_{st} + 1}{\sigma_{st}} \right) f(k_{jt}, l_{jt}, m_{jt}) - \tilde{\varepsilon}_{jt}
\end{aligned}$$

and its core component TFPRC:

$$\begin{aligned}\ln TFPRC_{jt} &\equiv \chi_{jt} + \left(\frac{\sigma_{st} + 1}{\sigma_{st}} \right) \omega_{jt} \\ &= \ln TFPR_{jt} + \frac{1}{\sigma_{st}} \ln Y_{gt}.\end{aligned}$$