Who Bear the Cost: Financial Friction and Labor Markdown*

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Abstract

China's financial markets are regionally fragmented with widely documented frictions, and firms of different characteristics are unevenly affected by the local financial market. Using a long series of bank branch distribution and firm performance data in China, we document that financial friction in the local market leads to significantly higher firm-level labor markdown, but has little impact on firms' product markup and profitability. This suggests that firms pass the impact of financial friction to the labor market by exploiting labor when faced with higher financial costs. We leverage the 2009 bank liberalization and employ an Instrumental Variable (IV) approach to address potential endogeneity concerns, and our results remain robust to these alternative empirical strategies. We find that the passthrough is more salient among low-skill-intensity firms because low-skill labor has lower bargaining power in the labor market; it is more significant among Private-Owned-Enterprises (POEs) because State-Owned-Enterprises (SOEs) are less prone to financial frictions. We also find that greater labor mobility facilitates the pass-through. Our findings highlight the *distributional* effect of financial friction in the economy: labor, especially the low-skilled ones, rather than capital, eventually bears the cost of financial friction.

Keywords: Labor Markdown, Financial Friction, Bank
JEL Codes:

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1 Introduction

Market power creates profits (Hall, 2018; De Loecker et al., 2020). Banks are the most important financial institutions, and bank loans are the dominant source of social financing in many countries. The banking sector is not perfectly competitive, and there are also significant trends in bank concentration in many countries (Janicki and Prescott, 2006; Laeven et al., 2014; Favara and Giannetti, 2017). Banks in less competitive financial markets make more profit by making fewer loans and charging higher interest rates (Wang et al., 2022; Whited et al., 2021), which means greater financial burdens for firms. The existing literature documents a robust negative relationship between bank concentration and firm entry and performance (Cetorelli and Strahan, 2006; Krishnan et al., 2015). However, firms do not bear the cost all by themselves. Saidi and Streitz (2021) show that higher credit concentration is associated with higher product markups, mainly because sharing the same lender induces less aggressive product market behavior among their borrowers, thereby internalizing the potential adverse effects of higher interest rates. In this paper, we propose an alternative novel channel by which firms transmit the cost through their market power– We show that the cost may eventually be passed to and borne by the laborers when firms can exercise significant labor market power.

In this paper, we exploit regional and time variations in China's bank concentration to study whether bank concentration affects firms' market power. We measure the market power of firms by comparing prices with marginal costs in the product market and by comparing wages with marginal product of labor in the labor market.[1] In perfectly competitive markets, the former should be equal to the latter. However, markets are not competitive–in our sample, there are substantial variations in the ratio between the two. Firms exhibit significant market power in both the labor market and the product market, and the firms' labor market power (as measured by labor markdown) is on average 1.5 times as large as that of the product market power (as measured by product markup). Thus, one may expect that firms find it relatively easier to exercise labor market power and pass the financial costs to the laborers compared to the product market. One innovation is that we separately study firms' power in the product and labor markets and examine how the two ratios respond to regional variations in bank concentration. We find that China's bank concentration has no significant effects on firms' product markup, but significantly affects firms' labor markdown, a measure of firms' monopsony power in the labor market.

add a paragraph on the importance of labor market power... in conjunction with the

[1] We rely on the standard production function estimation methods in the industrial organization literature to estimate the marginal costs of products. Recently, a growing line of literature has used similar methods to estimate the marginal product of labor, for example Brooks et al. (2021b,c).

global decline in labor share?

There are at least three reasons why China provides an ideal setting to study the impact of financial friction on the labor market. First, China's credit market is geographically segmented, so borrowers primarily obtain loans from local banks. In an integrated, nationwide market, there would be no reason to expect local bank concentration to affect local firms' labor market response—if local financing cost is too high, firms can finance in other cities, muting the local labor market response. Second, as with the financial market, the labor market in China is sufficiently segmented, and the laborers are mostly ununionized. The lack of labor mobility across regions and the weak labor union provide little protection to the employees, which gives the firms enough bargaining power to pass the cost of financial friction to the labor. This institutional feature allows us to zoom the focus on firms' labor market response and makes the study of labor market effect particularly relevant. Third, both the financial and labor markets have experienced dramatic changes in the past decade, providing us with plausible exogenous changes to corroborate the causal impact of financial friction on labor market outcomes and to understand its mechanism. On the financial market side, we exploit the bank liberalization in 2009—which encourages commercial banks to set up more branches and thus significantly increases the level of bank competition—to corroborate the causal impact of bank concentration on firms' labor markdowns. On the labor market side, we leverage changes in the Hukou restrictions at the city level to examine how labor supply and the corresponding changes in the labor's relative bargaining power affect the aforementioned pass-through channel.

Our baseline regressions exploit this regional variation in the levels of bank concentration to provide evidence of the association between firms' financial friction, measured by the bank branch HHI at the city-year level and their labor markdowns. We regress firms' product markup or labor markdown on the bank concentration of the cities where the firms are located. Our findings document a robust association between the level of bank concentration and firms' labor markdowns, while finding no statistically significant relationship between bank concentration and firms' product markups. The results are robust to a number of specifications with different fixed effects, to different measures of firm markdown and markup, to different measures of bank concentration, and to different sample periods covered by the Administrative Tax Records (ATR) and the Annual Survey of Industrial Firms (ASIF). To ascertain whether the relationship between city-year-level bank concentration and firm labor markdown can be interpreted causally, we further employ the instrumental variable (IV) strategy to isolate an exogenous shift within the banking sector. We construct two IVs for identification—whether the city mayor has working experience in the financial or fiscal sector and the average bank competition of the adjacent cities in the same province—and our results are robust using the IV specification.

We further employ a simple difference-in-differences (DID) method to analyze the impact of the 2009 financial market liberalization on the firms' labor markdown. The policy encourages local commercial banks and joint-venture banks to establish more branches, especially in cities with fewer branches before, and therefore, it significantly increases bank competition, reduces bank HHI, and creates exogenous variations in the change of bank competition across regions. We exploit this exogenous change in the regulation of bank branch establishment to identify the causal impact of bank concentration on firms' labor market response, and our findings confirm that increased city-level bank competition causally leads to lower firm-level labor markdown, while it has no significant effect on the firms' product markup.

However, not all firms, even those operating in the same market, are expected to be affected equally. Firms differ in their exposure to financial market frictions, their bargaining power against labor, and thus in their necessity and capacity to pass the cost to laborers in response to increasing bank concentration. We exploit firm-level heterogeneities and find that: First, compared to private-owned enterprises (POEs), state-owned enterprises (SOEs) are less affected by the level of bank concentration in their financing costs and debt structures. Thus, SOEs' labor markdown and product markup are much less responsive to variations in bank concentration than POEs. Second, large firms have larger bargaining power, and therefore, large firms increase labor markdown more aggressively than small firms in response to the elevated level of bank concentration. Third, low-skill labor has lower bargaining power, and thus, bank concentration has a larger impact on the labor markdown of firms in the low-skill intensity industries compared to firms in the high-skill intensity industries.

On the labor side, we examine several factors of the local labor market that shift the labor's bargaining power against firms to investigate the mechanism of the pass-through. First, we find that comparing a firm in a city that has witnessed labor protests with one in a city that has not, the former is more reluctant to pass the financial burden to employees through labor markdown. Second, comparing a firm in a city with stronger labor unions with one in a city with relatively weaker ones, firms in the former face more constraints in passing the financial burden to employees. Third, we leverage the city-level Hukou reform, which created exogenous variations in the labor supply in the local market because cities with relaxed Hukou restrictions attract more labor, and the more abundant supply weakens the relative bargaining power of labor. We find that enhanced labor mobility facilitates the passthrough for the firms in cities with relaxed Hukou restrictions, and the effect is more salient when the policy favors low-skilled laborers —aligning with our previous findings that firms in the low-skill intensity industries are more likely to pass the cost to the labor.

Lastly, we examine an alternative channel—bank concentration impedes firm entry and thus increases firms' market power in the labor market. Our finding on the effect of bank concentration on firm entry is against this alternative hypothesis.

Related literature Our paper primarily contributes to the growing literature on bank competition, financial market frictions, labor market monopsony, and labor share.

add a paragraph about cost pass-through— most of them focus on product market, we look at input market.

First, we contribute to the literature on bank competition and its real effects. Most of the literature focuses on the financial market impact—especially the impacts of bank competition on bank activities, for example, the amount of loans and the interest rates. They find that banks with market power can profit from manipulating interest rates and thus affect the transmission of shocks (Drechsler et al. (2017, 2021); Wang et al. (2022); Whited et al. (2021)). The findings are consistent with our premise that bank competition affects firms' financing costs. We provide consistent evidence using Chinese data and confirm that increased bank concentration is associated with higher borrowing costs for firms.

A smaller but growing line of literature studies how firm activities are affected by bank competition. Cetorelli and Strahan (2006) show that increasing bank competition facilitates the entry of firms. Krishnan et al. (2015) show that bank competition increases firms' TFP. Among the papers in this strand of literature, our paper is closely related to Saidi and Streitz (2021), which studies the impact of bank concentration on the product markup of firms in the United States. Exploiting concentration-increasing bank mergers and variation in banks' market shares across industries, they show that higher credit concentration is associated with higher interest rates and higher product markups, mainly because that greater incidence of competing firms sharing common lenders that induces less aggressive product market behavior among their borrowers, thereby internalizing potential adverse effects of higher rates. Interestingly, we find that Chinese firms respond to bank concentration by increasing the labor markdown and not significantly changing the product markup. We conjecture the difference between the findings in the context of the two countries lies in the relative bargaining power of employers versus employees. We test this labor market mechanism with regional variations in labor market conditions and confirm that the pass-through is indeed strengthened by more abundant supply and weakened by the presence of labor protests and labor unions. To the best of our knowledge, this paper is the first study on the labor market effect of bank concentration and provides the first systematic empirical evidence on the transmission of bank concentration to labor markdown through firms' bargaining power.

Zooming into China's banking system, it underwent significant reforms and liberalizations over the past decades. China is an ideal case for studying bank-firm relationships because bank loans are the dominant source of financing for Chinese firms and households (Sun (2020)). Gao et al. (2019) document that increased bank competition improved loan contract terms and loan quality. Other studies also show that China's financial development has had significant impacts on interest rates and credit allocation (Cong et al. (2019); Huang et al. (2020); Liu et al. (2021); Gao et al. (2019); Hsieh and Klenow (2009); Song and Xiong (2018)). Relatively little is known how China's firm activities were affected by financial development. More importantly, in sharp contrast to the rising concentration in the developed countries, we document that China's banking concentration has decreased in the recent decade, which is mainly driven by the extensive margin bank branch expansion. Our contributions are twofold: First, we document that variations in China's bank concentration significantly affected firms' power in the labor market, and the effects are unevenly distributed among the state and private sectors. Second, by focusing on China, we develop a more comprehensive understanding of the effect of *decreasing* bank concentration. This is particularly relevant when people think about the counterfactual policy implications of the rising trend of bank concentration.

We also contribute to a growing line of literature on labor monopsony by documenting bank concentration as a determinant of labor markdown. Card et al. (2018), Gouin-Bonenfant (2022), Berger et al. (2022), and Lamadon et al. (2022) study the sharing of rents in labor markets with search and matching frictions. Yeh et al. (2022) estimate the labor markdown for U.S. firms using similar methods to ours and document the evolution of labor markdown in the U.S. Our measure for labor markdowns follows Brooks et al. (2021c), which also focuses on labor markdown in India. Related, Brooks et al. (2021a) find that infrastructure developments reduce labor markdown in India. Our results are broadly consistent with theirs in that improvements in firms' business environment reduce labor exploitation.

A growing body of macrofinance literature studies the relationship between financial friction and labor market outcomes. Hall (2017), Belo et al. (2017), Kehoe et al. (2019), Kehoe et al. (2023) establish theoretical linkages between asset prices and unemployment. Mian and Sufi (2014), Chodorow-Reich (2014), Berton et al. (2018), Siemer (2019), Luck and Zimmermann (2020), Chodorow-Reich et al. (2021), Mehrotra and Sergeyev (2021) empirically show that variations in the financial market conditions affect the labor market. Our empirical findings suggest that variations in firms' market power can be a new channel through which the financial sector affects the labor market.

The remainder of the paper is organized as follows. Section 2 describes the institutional background of the financial market and presents the changing pattern of labor monopsony power over time. Section 3 describes the data and the construction of key measures. Section 4 presents our empirical strategy and the main empirical results. Section 5 discusses and tests several potential alternative mechanisms. Section 6 concludes.

2 Background

2.1 Financial Market Reform

China's financial system is dominated by banks, including three policy banks, one postal bank, five state-owned commercial banks, 12 joint-equity banks, 40 locally incorporated foreign banks, 133 city commercial banks, and more than 2,000 rural commercial banks or credit cooperatives. The bank sizes are highly unequal. The five state-owned banks control 40% of total bank assets, joint-equity banks 19%, local banks 30%, and foreign banks 1%.

Bank loans dominate China's financial system's financing to the real economy. During our sample period, 61 to 79 percent of annual Aggregate Financing to the Real Economy was provided by bank loans and acceptance bills[2]. Given banks' pivotal roles in China's financial system, competition among banks greatly affects financial frictions in China's economy.

China's credit market is geographically segmented, so borrowers mainly obtain loans from local banks(Huang et al., 2020). Geographic segmentation arises from two sources. First, city and rural banks rarely operate outside their own cities or provinces. Local banks were prohibited from doing business outside their province of origin before 2006. Reforms between 2006 and 2009 removed the restrictions, but very few inter-province licenses were actually approved.

Second, the policy banks and state-owned banks also operate locally. The local branches of state-owned banks have substantial autonomy in making decisions, greatly affected by the pressure to lend to local governments and state-owned enterprises (Dobson and Kashyap (2006)). Investment projects are driven mostly at the local level and funded by banks. Local officials often have more authority over investment project approval than credit officers in the head offices of big banks (Roach (2006)).

The geographical segmentation of the banking sector is manifested in the regional dispersion of firms' financing costs. Figure 3c plots the average financing cost (measured as the city average of firm-level total interest payment/total outstanding debt) across the country, showing significant regional differences even within each province. Within each geographically segmented market, the bank system is characterized by its uneven distribution of credits. Using firm-level data, Bai et al. (2018) document that state-owned firms (SOE) have higher leverage and pay lower interest rates than non-SOEs, and among privately owned firms, small firms have lower leverage, pay higher interest rates, despite that they grow faster, and

[2]Entrust and trust loans contributed another 8 to 26 percent.

face a higher marginal product of capital (MPK) than large firms.

In the recent decade, China's banking sector has gone through dramatic changes characterized by a significantly decreasing concentration level, especially at the extensive margin—Figure 1 plots the number of bank branches for the big five banks and other banks separately, as well the evolution of bank branch HHI over the period of 2000-2015. As shown in the figure, the number of bank branches doubled over the past two decades, leading to a significant drop in the bank HHI at the city level. The increase in bank branches is mainly driven by the expansion of commercial banks.

[Figure 1 about here.]

The 2009 Bank Branch Liberalization Despite the overall trend of bank branch expansion, China's banking sector is highly regulated. The China Banking Regulatory Commission (CBRC) was founded in March 2003 to supervise the banking sector. In 2018, the CBRC and China Insurance Regulatory Commission merged and became the China Banking and Insurance Regulatory Commission (CBIRC), which the National Administration of Financial Regulation replaced on March 10, 2023. The CBRC placed strict restrictions on opening branches for non-state-owned banks.

In 2006, the CBRC announced that the joint equity banks and local commercial banks could only apply for opening one branch in one city at a time, and the banks could not submit another branch opening application before the current one had been approved or rejected by the CBRC. Moreover, the CBRC capped the total number of branches in each city. By the end of 2008, more than 69% of the cities had no joint-equity bank branches, and the average number of joint-equity bank branches in a city was 12. On the contrary, the five state-owned banks had branches in more than 98% of the cities, and the median number of state-owned bank branches was 125. These regulations were strongly biased towards the state-owned banks and reduced competition between state-owned and non-state-owned banks.

In April 2009, the 2006 restriction was removed by the CBRC as a vital policy liberalization. Joint equity banks were allowed to enter cities where they had already set up branches. They could also freely enter a province's cities if they had branches in the provincial capital. In these qualified cities, joint-equity banks could freely open branches without any caps on the number of branches. As a robustness check for our baseline regressions, we exploit this policy liberalization to perform a standard difference-in-differences analysis. Parallel to our exercise, Gao et al. (2019) exploit the same policy change to study the effects of bank deregulation on bank loans and firm activities.

2.2 Labor Market Monopsony

Worldwide, the decline in labor's share of aggregate income has been extensively documented and is related to an increase in firms' market power (Autor et al., 2020; Kehrig and Vincent, 2021). This increase in market power can decrease labor's share through a direct increase in markups, but also through an exercise of monopsonistic market power against labor (Brooks et al., 2021c). However, in China, the pattern of decreasing labor share and increasing labor markdown over time has been reversed in recent years. In Figure 2, we present the average labor markdowns across Chinese firms using the Administrative Tax Survey data for the period 2009-2015.[3] The estimated labor markdown continues to increase during 2009-2011, which is consistent with the reported declining share of labor's income and the increased labor market power of firms in early period of China (Brooks et al., 2021c). But more importantly, and more interestingly, we find that in recent years labor markdowns have started to fall, indicating firms' labor monopsony power having been declining. This reversal trend is related to institutional changes in the labor market, such as the gradually loosened household registration (*hukou*) system in China. In this paper, we leverage the regional variation of this institutional change of the labor market to construct instrumental variables that allow us to identify the causal impact from a novel channel: financial frictions in the local market would substantially affect firms' labor monopsony power and firms would pass those financial burden to labor by exploiting workers.

[Figure 2 about here.]

3 Data and Key Measures

3.1 Data

Administrative Tax Survey (ATS) The main data set that is the ATS that contains administrative enterprise income tax records compiled by the Chinese State Administration of Tax (SAT) for the years 2008-2015.[4] The data set covers a representative sample of more than 1 million firms from stratified sampling. The SAT in China is the counterpart of the Internal Revenue Service in the US. For tax collecting and auditing purposes, they collect firm-level records of tax payments and other financial statement information used in tax-related calculations. The advantages of the tax data are threefold. First, it is representative

[3] The estimation method of labor markdown is elaborated in detail later in the measurement section (see Section 3.3).

[4] The data set has been previously used in many influential studies, e.g. Chen et al. (2021),Chen et al. (2023), etc.

with wide coverage. The stratified sampling method of the data set ensures that large firms are included every year and that smaller firms are included on a rotating basis. Second, as administrative data, it is less subject to the potential measurement error problem than the self-reported data. Third, it has detailed historical information on a wide spectrum of tax-related information about the firms, including their total production, sales, inputs, employment, wages, etc. This allows us to calculate the firms' markup and markdown, and examine the firms' performance in a longer time horizon and in more dimensions.

Annual Survey of Industrial Firms (ASIF) The ASIF is conducted by the National Bureau of Statistics of China (NBSC). The database covers all state-owned enterprises (SOEs), and non-state-owned enterprises with annual sales of at least 5 million RMB (about $750,000 in 2008). It is one of the firm-level data sets that contain the most comprehensive information on firms in China[5]. Between 1999 and 2007, the approximate number of firms covered in the NBSC database varied from 162,000 to 411,000. The number of firms increased over time, mainly because manufacturing firms in China have been growing rapidly, and over the sample period, more firms reached the threshold for inclusion in the survey. The ASIF supplements the ATS data in two folds: First, the ASIF covers different sample periods as ATS. Second, the ASIF has a more comprehensive coverage of manufacturing firms than the ATS. As such, we also use this data set to cross-validate our findings from the ATS data.

Since there is a great variation in the number and sample of firms in the ATS and the ASIF database, we used an unbalanced panel to conduct our empirical analysis. For industries, we use the adjusted 4-digit industrial classification from Brandt et al. (2012). We construct real capital stocks by deflating fixed assets using investment deflators from China's National Bureau of Statistics and a 1998 base year.

Bank Branch Data The data on bank branches are scraped from the China Banking and Insurance Regulatory Commission's (CBIRC) website. CBIRC's website discloses information on the address, employment size (measured by the number of employees with social security payment), entering date, and exit date (if any) of every bank branch that holds a financial permit. We use the records of the entering and exit years to identify the time period that each bank branch contributes to our concentration measure. Our bank branch data contains over 200,000 branches of approximately 2,800 banking financial institutions established since 1948.

[5]These data have been previously used in many influential development studies, e.g., Hsieh and Klenow (2009),Song et al. (2011), etc.

3.2 Measuring Financial Friction

HHI We measure financial friction with bank HHI at the prefecture city (henceforth, "city")-year level. Prefecture cities are large. For example, in 2009, the average population of a prefecture city in our sample was 3.17 million. The land area ranges from 1,113 to 391,817 square kilometers, and the average land area is 19,793 square kilometers (about the size of Slovenia). We compute HHI for city c and year t according to the following formula:

$$HHI_{c,t} = \sum_{b \in c} \left(\frac{\text{\# of branches of bank } b \text{ in year } t}{\text{\# of all branches in city } c\text{, year } t} \right)^2. \tag{1}$$

Our HHI measure is the sum of squared branch shares of all banks in a city each year. We assign to each firm in our data the HHI of the city and the year in which it operated and was observed. The branch HHI only captures the extensive margin entry and exit of bank branches and ignores branch-level heterogeneities—A new branch, regardless of its size, contributes equally to the branch HHI. To address this concern, we construct an alternative measure of bank concentration—the employment-share HHI, which is computed using the employment share of each bank within the city according to the following formula:

$$HHI_{c,t} = \sum_{b \in c} \left(\frac{\sum_{b(i)} \text{Employment of branch } b(i) \text{ of bank } b \text{ in year } t}{\text{Total employment of all branches in city } c\text{, year } t} \right)^2. \tag{2}$$

However, the branch employment data covers fewer bank branches than the branch establishment's data, so we use the bank-branch-share HHI in our main empirical exercise and use the employment-share HHI as a robustness check. We find no qualitatively different results by using the two measures.

Financial Friction and Firm Borrowing Constraint To affirm that the bank branch HHI is a good measure for financial frictions, we examine the relationship between HHI and firms' borrowing costs and between HHI and firms' book leverage—both measured at the firm-year level. Borrowing cost is defined as the ratio between a firm's annual interest payment and annual outstanding debt. Leverage is defined as the ratio between a firm's outstanding debt and total equity.

Table 1 columns (1)-(2) present the relationship between bank concentration and firms' borrowing costs, for the sample of SOEs and POEs separately. Column (1) shows that the city's bank concentration (as measured by bank branch HHI) is positively associated with the POEs' borrowing cost, suggesting that POEs face higher financial costs in cities with a higher level of bank concentration. The estimated coefficient is statistically significant at the 1% level. Column (2) shows that the city's bank sector concentration is negatively correlated with the SOEs' financing cost, in sharp contrast with that for the POEs, though the correlation is statistically insignificant.

Furthermore, columns (3)-(4) present the relationship between bank concentration and firms' financial structure as measured by the firms' leverage ratio, for the sample of SOEs and POEs separately. For the firm's leverage ratio, we can use a much larger sample based on the firm registration and inspection data. According to the Chinese government regulation, local SAIC offices require all firms to report their financial information annually for the purposes of an inspection procedure to ensure that firms are operating normally and running businesses legally. The inspection information includes the firm's assets, liabilities, total sales, total profit, net profit, and total taxes, and thus, we can calculate the firm-level debt structure for the universe of registered firms. It shows a similar pattern as with the interest rate. Column (3) shows that the city's bank concentration is negatively associated with the POEs' leverage ratio, suggesting that POEs, on average, have a lower leverage ratio in cities with a higher level of bank concentration. The result is consistent with that in column (1), as firms facing higher financial costs are harder to finance and thus have lower debt levels on average. Column (4) shows that the city's bank sector concentration negatively correlates with the SOEs' financing cost, though statistically insignificant.

Overall, the results provide consistent evidence that the HHI is a good measure for the local market's financial friction, which projects well onto firms' financial performance. Bank concentration is robustly positively correlated with the POEs' financing cost, and if there were any effect on the SOEs, the effect is the opposite. This is consistent with the literature that SOEs are well connected with and favored by the bank sector, and the data suggests that this favoritism on the SOEs is more so when the bank sector lacks competition.

[Table 1 about here]

3.3 Measuring Labor Markdown

Labor markdown is defined as the ratio of the value of the marginal product of labor to wage in real terms. Product markup is the ratio of the product price to the value of the marginal cost in real terms.

Our method of estimating labor markdown and product markup follows Brooks et al. (2021c). We estimate markup and markdown using three different approaches. The first two approaches follow De Loecker and Warzynski (2012), who use the first-order condition for any flexibly-chosen, price-taking input to derive firm-specific markup as the ratio of the factor's output elasticity $\theta^M_{i,t}$ to its firm-specific factor payment share $\alpha^M_{i,t}$:

$$\mu^M_{i,t} = \frac{\theta^M_{i,t}}{\alpha^M_{i,t}}. \tag{3}$$

We take materials as the flexibly chosen input and denote it by M in superscript. The factor payment share is observed in the data, but the output elasticity needs to be estimated.

Our first method of estimating $\theta^M_{i,t}$ derives it from the production function estimation of Ackerberg et al. (2015) as in De Loecker and Warzynski (2012). This approach estimates translog production functions that can be easily solved for elasticities. Since this is a standard way of estimating markups, we use it as the baseline measure of markups and markdowns and label it as "DLW".

Our second method assumes that the production function is constant returns to scale and uses the gross profit margin to estimate markups. The formula for markups is

$$\mu^M_{i,t} = \frac{sales}{costs}. \tag{4}$$

This approach assumes that the downward-sloping demand fully determines the firm size but is less restrictive along other dimensions. For example, compared to DLW, it allows for firm-specific time-varying production functions. We label this approach "CRS", standing for the constant returns to scale assumption.

Our third method uses the same markup formula as DLW, but does not estimate the elasticity $\theta^M_{i,t}$. Instead, it simply assumes that the production function is Cobb-Douglas with respect to materials, i.e., $\theta^M_{i,t} = \theta^M$. Following Brooks et al. (2021c), we choose $\theta^M = 0.8$. We label this approach "CD", which stands for Cobb-Douglas.

In each case, markups are measured with substantial error. We therefore winsorize 3 percent in both sides of the tails of each 2-digit industry in each year.

3.4 Summary Statistics

Table 2 presents summary statistics for the key variables of interest in the ATS sample.[6] Panel A reports the statistics for the firms at the firm-year level. Our baseline measure of labor markdown is borrowed from Brooks et al. (2021c), which is derived from the production function estimation method of De Loecker and Warzynski (2012). The mean markdown is 10.69, and it varies substantially in the sample. The standard deviation of the markdown is 31.22, about 3 times the mean value. We also derive the labor markdown from constant

[6] A similar summary statistics table for the ASIF sample is presented in Table A2 in the appendix.

returns to scale or Cobb-Douglas production functions. Despite different estimation methods, the sample moments of the respective markdown measures are similar. Panel B reports the statistics at the city-year level. The average bank branch HHI is 0.13 with a standard deviation of 0.09, and the HHI measured with the banks' employment share has an average value of 0.16 and a standard deviation of 0.12. On average, a city has 586 bank branches, most of which consist of commercial bank branches, followed by branches of the big five bank branches, and other types (e.g., joint-venture, rural, etc.) only constitute a very small proportion.

In the Appendix, we present the respective summary statistics for the ASIF sample. The moments of the markdown and markup measures in the tax survey and ASIF samples are comparable.

[Table 2 about here]

We present the geographical distribution of key variables in Figure 3. Each panel shows the city-level average (over firms and time) of the corresponding variable. Darker colors indicate larger numerical values, and white areas are missing observations. The cross-region geographical distribution yields several interesting patterns. In general, the less developed northern and western regions exhibit higher bank concentration, higher borrowing costs, and higher labor markdowns. Panel 3a shows the distribution of city-level bank branch HHI. A larger HHI indicates higher bank concentration and less competition. Overall, cities in western and northern China have higher bank concentration. Despite the general pattern, some cities in more developed eastern China also have high HHI values. For example, Yangzhou, which is a city in Jiangsu province, had an HHI of 0.21 in 2009, among the highest ten percent. Panels 3b and 3c show the geographical distributions of the DLW labor markdown and firms' borrowing costs. Firms in northern China, on average, have higher labor markdowns, consistent with the higher bank concentration in these regions.

[Figure 3 about here]

4 Empirical Results

This section introduces our empirical strategy and presents the main findings to establish the causal relationship between regional financial friction and firms' labor markdown.

4.1 Baseline Results

We estimate the equation

$$\ln \mu^L_{f,t} = \beta_0 + \beta_1 HHI_{c,t} + \beta_2 \ln \mu^M_{f,t-1} + \Gamma' X_{f,t} + \alpha_f + \alpha_t + \alpha_{prov,t} + \varepsilon_{f,t}, \tag{5}$$

where $\ln \mu^L_{f,t}$ denotes log labor markdown for firm f in year t, and $HHI_{c,t}$ denotes the bank HHI for the city c in which the firm locates. We control for the log product markup, $\ln \mu^M_{f,t-1}$, because it is negatively related to the labor markdown by construction. The firm-level control variables, $X_{f,t}$, include log capital stock, log employment, and log material inputs. Furthermore, we control for firm, year, and province-year fixed effects.

Our identification strategy compares the average firm in a high-HHI city-year pair with the average firm in a low-HHI city-year pair. In addition to bank competition, other confounding factors affecting labor markdown include firm, industry, and provincial characteristics. We use fixed effects to control for the unobserved characteristics. Firm fixed effect controls for unobserved firm-level heterogeneities, such as the firm's size, production technology, market structure, political connections, employment structure within the firm, etc. Year fixed effect absorbs the national trend in financial liberalization. Province-by-year fixed effect controls for the regional time-varying changes in labor market conditions, business environment, and other provincial-level policy changes.

Table 3 reports results for the baseline regression. The coefficients are estimated using OLS with fixed effects. The sample period is from 2009 to 2015, and firms are observed annually. The dependent variable is the DLW labor markdown, and we also include the DLW product markup (1-year lag) as an independent variable to control for the correlation between the two variables in the estimation method. We also repeat the exercise with the DLW product markup as the dependent variable to distinguish the effect of bank HHI on labor markup and that on the firms' product markup. Columns (1), (3), and (5) report the regression results for labor markdown, and columns (2), (4), and (6) report the regression results for product markup accordingly.

In columns (1) and (2), we report the regression results using the DLW measures of markdown and markup as independent variables. An increase in HHI by one standard deviation (0.09) is associated with an 8% increase in the labor markdown, and the coefficient is statistically significant at the 5% level. On the other hand, bank HHI has no statistically significant effect on the firms' product markup. The results jointly suggest that the cost of financial friction is solely borne by labor and is hardly passed to consumers via product markup. In other words, firms are fairly competitive in the product market but have significant market power in the labor market. Thus, it is not easy for them to adjust prices, but exploiting the labor in response to higher financial frictions is relatively easy. It is worth noting that this does not imply that consumers bear no cost— rather, they bear the cost through their loss in labor income. In the remaining columns, we report results from regressions using the CRS and CD measures of markdown and markup. In all regressions, bank concentration has a positive marginal effect on labor markdown and an insignificant marginal effect on product markup.

[Table 3 about here]

In a robustness check, we measure bank concentration based on bank branch employment shares. We repeat the exercises in Table 4. The results remain qualitatively robust, and the coefficients on the employment share HHI are similar to those on the branch HHI— an increase in HHI by one standard deviation (0.09) increases the labor markdown by approximately 8%. Furthermore, the values of the coefficients on the employment share HHI are stable across all markdown and markup measures.

In summary, our baseline regressions establish the positive relationship between bank concentration and labor markdown. The firms pass the cost of bank concentration to employees by reducing wages per unit of marginal labor output.

[Table 4 about here]

We further cross-validate our results using the ASIF data or keep the subsample of the manufacturing firms in the tax survey data. The results are reported in Table A1, which remain robust.

4.2 Instrumental Variable (IV) Approach

Because of the aggregate nature of our explanatory variable, bank concentration at the city-year level, one may be concerned that it captures other underlying developments or socioeconomic conditions across regions as well. While we control for a host of fixed effects, one potential issue with the fixed effect model pertains to the possibility of a correlation between bank concentration and latent alterations at the city level, which could concurrently influence firms' labor markdown. This entails that both the HHI and labor markdown may be associated with time-varying unobservable factors. To illustrate, if concealed shifts in a city's labor market policies impact its labor supply, the implications for financial friction measurement and firms' labor markdown can be intertwined. Specifically, a more abundant labor supply might attract new firms, increasing bank branches in the local market. This augmented labor supply may also concurrently weaken labor bargaining power, consequently elevating labor markdown levels.

To mitigate potential endogeneity issues, we employ an instrumental variable (IV) approach that allows us to isolate an exogenous shift within the banking sector. We employ two distinct instrumental variables: firstly, the average bank HHI of neighboring cities in the same province; and secondly, a binary indicator taking the value 1 if the city's mayor possesses prior work experience in either the financial sector or fiscal system.

First, with each city treated as a separate market, the concentration indices of neighboring cities are not likely to affect the local firms' financing options or the local labor market. In contrast, the concentration indices could be associated with the value of neighboring cities. Cities with intense competition could drive banks to turn to those with fewer competitors by opening new branches, which could affect the local concentration indices. In addition, the similarity of government regulation among nearby regions will also lead to the correlation of competition indexes. Consequently, the average concentration indices of neighboring cities are correlated with local concentration indices but uncorrelated with local firms' financing costs or labor markdowns, which makes these indices good instruments.

The second IV, the local officials' experience in the financial sector, is unlikely to affect the local firms' labor market power because it is unrelated to any labor market conditions. However, it could be associated with the financial market condition because local officials' personal experience may shape their policy preferences and political resources for policy tools, and thus further affect local policies to foster bank competition. More specifically, officials with working experience in the financial sector usually possess some experience in the big-five state banks rather than the small local banks, and they also have better political connections in the financial system to strengthen the local consolidation of the banking sector. Consequently, one may expect that cities whose local officials have experience in the financial sector tend to have higher bank concentrations.

Table 5 reports the first-stage regression results. Columns (1) and (2) only include one of the two IVs, and column (3) includes both IVs. The results suggest that the city's HHI is highly positively correlated with its neighbor's HHI, and the local city leaders' working experience in the financial or fiscal sectors is also positively correlated with the city's bank concentration. Coefficients for both variables are statistically significant at the 1% level, suggesting a strong first stage.

[Table 5 about here]

Table 6 reports the results for the IV estimation. The results remain qualitatively robust, and the coefficients on the bank concentration HHI are positive and slightly smaller in magnitude than those in the baseline regression. The p-values for the Sargan over-identification test are all greater than 0.1, suggesting that the null hypothesis that the two IVs are both exogenous cannot be rejected.

[Table 6 about here]

4.3 Exogenous Bank Expansion

We further employ a simple difference-in-difference (DID) method to analyze the impact of the 2009 financial market liberalization, which significantly increases bank competition and reduces bank HHI, on the firms' labor markdown. It is beneficial to recap the 2009 bank reform as detailed in Section 2.1. The most important characteristic of the reform is to remove the previously strict cap on the number of branches operated by joint-equity banks and local commercial banks. The reform encourages commercial banks to set up more branches in cities that had fewer branches and less competition in the banking sector[7]. Thus, one may expect cities with fewer branches before the reform to be more exposed to the reform and, therefore, exhibit a larger decrease in the bank concentration. Our identification strategy relies on the heterogeneity across cities in the pre-reform commercial bank branch prevalence. To be more specific, we use the log of the number of commercial banks' branches in the year 2008 (the year before the reform) as the measure for treatment intensity—the more branches there were before the reform, the lower the treatment intensity is; and we use the year 2009 as the treatment starting year. The difference-in-differences (DID) analysis compares the labor markdown and product markup of firms in cities with fewer pre-reform bank branches—i.e., high-treatment intensity cities—to those in low-treatment intensity cities, before and after the exogenous bank expansion reform in 2009.

The dependent variable is bank HHI?Table A4 first verifies the validity of the DID design at the city-year level. The dependent variable is bank HHI for a city in each year. Column (1) controls for city and year fixed effects, and column (2) further controls for province-by-year fixed effects. The coefficients estimated for the DID term are positive and statistically significant, suggesting that cities with more pre-reform commercial bank branches on average have a smaller decrease in bank HHI, and thus a smaller increase in bank competition, after the reform.

Our firm data start from 2008 and only covers 1 year before the reform, so we cannot test the parallel trend assumption at the firm level. Instead, the bank data start from 2005. Figure A1 presents the dynamic effect of the reform on local bank HHI. The pre-reform insignificant coefficients provide empirical support for the parallel trend assumption at the city level.

[7] See https://www.gov.cn/gzdt/2009-04/30/content_1301338.htm

Table 7 reports the regression results for the DID test. The results corroborate our findings— enhancing bank competition leads to lower firm-level labor markdown. To be more specific, the interaction term of the DID test is positive and statistically significant, suggesting that firms located in cities with more commercial bank branches before the reform had a smaller decrease in labor markdown after bank branch deregulation.

[Table 7 about here]

4.4 Heterogeneity in the Pass-through

To better understand the sources of the pass-through from the financial market to the labor market, we examine the heterogeneities of the pass-through with firm-level characteristics. We provide evidence that the strength of pass-through crucially depends on 1) the extent to which firms are affected by the financial frictions, and 2) the firms' relative bargaining power and their ability to pass the cost to the labor.

SOE vs. POE As shown in Section 3.2, SOEs are not sensitive to the changes in the banking sector HHI— they face little financial friction and can finance at a low interest rate regardless of the bank concentration. As SOEs are not affected by bank concentration in their financing, their labor markdown should not be affected either. We test the hypothesis by interacting the bank HHI with a dummy variable equaling 1 for SOEs. The results are reported in Table 8. The coefficients of HHI remain positive and statistically significant, confirming that POEs in cities with lower bank competition have higher labor markdown. Moreover, the coefficients of the interaction terms are negative, suggesting that SOEs are much less affected by the pass-through channel. In our baseline measure, the interaction term reduces the marginal effect of HHI by 79%, suggesting that state-owned enterprises' labor markdowns are only 21% as sensitive to bank concentration as non-state firms'. The results are qualitatively robust across different measures of the labor markdown: DLW, CD, and CRS.

[Table 8 about here]

Firm size We test whether larger firms are more able to increase the labor markdown when the banks are more concentrated. We use the log of the firms' registration capital to measure the firm size and interact it with the bank branch HHI.

Table 9 shows that the marginal effect of bank concentration on labor markdown is larger for larger firms. The coefficients of HHI and the interaction between HHI and log registration capital are quantitatively similar across all specifications of the labor markdown: DLW, CD, and CRS. The mean value of log registration capital in our sample is 6.68, and the standard deviation is 2.22. For an average firm, the marginal effect HHI on the labor markdown is 0.8 for the DLW markdown ($0.199 \times 6.68 - 0.504$), 0.56 for the CD markdown ($0.179 \times 6.68 - 0.632$), and 0.49 for the CRS markdown ($0.117 \times 6.68 - 0.295$). When the firm size increases by one standard deviation, the marginal effect of HHI on the labor markdown increases by 0.44 (0.199×2.22).

[Table 9 about here]

Skill intensity Skilled workers are relatively harder to exploit than unskilled workers. We test this hypothesis by interacting an industry-level skill measure with the bank branch HHI. The measure of skill intensity is borrowed from Belo et al. (2017) and is calculated at the 3-digit industry level for US firms. The skill intensity of an industry is defined as the percentage of high-skill workers—i.e., those who work in occupations requiring a high level of training and preparation—in that industry. We then use the industry correspondence to map the industry-level skill intensity to Chinese firm data.[8]

Table 10 shows that firms in high-skill industries pass less financial burdens to the labor markdown. We use three measures of HHI: DLW, CD, and CRS. The coefficients on HHI and the interaction term are both robust across all specifications. In all specifications, the interaction between HHI and skill intensity is negative, indicating a weaker pass-through for skill-intensive industries. The results are consistent with the conventional wisdom that high-skill workers have higher bargaining power against the firms. Moreover, high-skill labor is more mobile across regions and firms (Fang et al., 2023)—if firms exploit them too much, they can relocate more easily to other regions as compared to low-skill labor—weakening the firms' ability to pass the financial costs to the labor.

[Table 10 about here]

5 Inspecting the Mechanism

Why do firms respond to elevated financial frictions by exploiting labor rather than passing the cost to consumers in the product market? The firms' capability to pass the costs to the labor market crucially depends on the institutional features of China's labor market. The labor market in China is sufficiently segmented, and the laborers are mostly

[8] The industry correspondence is available at https://www.census.gov/naics/reference_files_tools/2022_NAICS_Manual.pdf.

ununionized. The lack of labor mobility across regions and the weak labor union provide little protection to the employees, which gives the firms enough bargaining power to pass the cost of financial friction to the labor. In this section, we leverage the regional variations in the labor market conditions to investigate this pass-through channel.

5.1 Labor Bargaining Power: Evidence from Labor Protest and Labor Union

A key determinant of the effects of bank concentration on labor markdown is the relative bargaining power between employers and employees. When the employees' bargaining power strengthens, we expect to see a reduction in the coefficient on bank HHI. We exploit regional variations in labor protests and the presence of labor unions to test this hypothesis.

The labor protest data come from China Labour Bulletin, a non-government organization based in Hong Kong that supports labor movements in China. China Labour Bulletin keeps records of labor movements after 2011, including information on the city, year, industry, and reasons for the protests. From 2011 to 2015, the dataset contains 4,845 labor protest cases, among which 3,463 (71%) were related to wages.

When firms just experienced or witnessed labor protests, they may be more cautious in passing the cost to the labor. We create a dummy variable for a city-year pair that indicates whether labor protests happened in the city-year and interact it with the city-year level bank HHI. Table 11 shows the results. The bank HHI has a positive coefficient, indicating a positive relationship between bank concentration and labor markdown. The interaction between the bank HHI and the protest indicator has a negative and significant coefficient. Comparing a firm in a city that has witnessed labor protests with one in a city that has not, the former is more reluctant to pass the financial burden to employees through labor markdown.

[Table 11 about here]

Second, the presence of labor unions may also strengthen the relative bargaining power of the labor. We collect the provincial-year level labor union data from China Labor Statistical Yearbooks 2008-2015, which contains information on the province-level number of labor unions in SOEs and POEs separately.

We interact the city-year-level bank HHI with the log number of POE labor unions and the log number of SOE labor unions separately. Table 12 shows the results. The interaction between the bank HHI and the log POE labor union number has a negative and significant coefficient. Comparing a firm in a city that has stronger labor unions with one in a city that has relatively weaker ones, firms in the former one face more constraints in passing the financial burden to employees through labor markdown. On the other hand, the interaction between the bank HHI and the log SOE labor union number is statistically insignificant, confirming that SOEs are merely affected by the pass-through channel.

[Table 12 about here]

5.2 Labor Supply and Bargaining Power: Evidence from Hukou Reform

Second, we examine the role of labor mobility restrictions in facilitating the pass-through. The relative bargaining power between employers and employees crucially depends on the abundance of labor— when the labor supply increases, employers gain stronger power in setting wages and thus may strengthen the pass-through channel, and vice versa. We exploit the exogenous changes in labor mobility restrictions, i.e., the Hukou reform, to test this hypothesis. When the labor market exhibits overall mobility restrictions, cities that relax the mobility restrictions attract more labor into the local market, which may strengthen the local firms' relative bargaining power.

Hukou is a system of local registration that severely restricts labor mobility in China, particularly rural farming labor mobility. Before 1978, workers were prohibited from working outside their region/registration category. Since then, the restrictions have been relaxed incrementally, with reforms being introduced gradually across different cities. The relaxation of the restrictions created an exogenous shock to the local labor market— labor can freely move into the local market, and thus, the labor supply significantly increases after the reform. We manually collect information on the local prefecture-level implementation of the Hukou reform passed at the national level from several sources. We first collect all migration-related policies across multiple platforms to build our policy dataset. The primary sources of government regulation documents are from Beidafabao (PKUlaw),[9] various governance discussion papers and official government websites, government gazettes, repositories of laws and regulations, as well as documents provided by relevant administrative units. We also complement these sources by directly searching the keywords through the search engine and historical news. The roll-out of the Hukou reform provides significant spatial and temporal variation in policy-based labor mobility costs. For each reform, we obtain information on the type of policy, the target group (origin, demographics, employment, and financial condition) to which the policy applies, and the scope and strength of the migration

[9] The website is www.pkulaw.com.

cost relaxation/tightening. This allows us to broadly characterize the Hukou reform into two categories— non-restrictive relaxation, which imposes no or very little restrictions on the conditions for a local Hukou, and skilled-biased relaxation, which imposes restrictions on the individuals' education, skill, or investment for a local Hukou.

Table 13 reports the effect of Hukou reforms on the firms' pass-through. We interact the city-year-level bank HHI with a dummy variable indicating whether the city has implemented the Hukou reform. The results suggest that Hukou reform strengthens the pass-through. Cities with relaxed Hukou restrictions attract more labor, especially low-skilled labor, into the local labor market, and the more abundant labor supply benefits the firms and increases their bargaining power in wage setting. In cities without Hukou reform, the coefficient on HHI is 0.89, similar to the corresponding coefficient in the baseline regression. On the other hand, the marginal effect of HHI on the labor markdown for firms in cities with relaxed Hukou restrictions is 1.50 (0.89+0.61), 69% larger than in cities without.

[Table 13 about here]

We then examine the effect of skill-biased Hukou reform only by replicating the exercise with the skill-biased reform dummy. Table 13 reports the effect of the skill-biased Hukou reforms on the firms' pass-through. The interaction terms are positive but statistically insignificant, and the magnitudes are much smaller than those of the general Hukou reform. This further corroborates our findings that skilled labor is harder to exploit, and thus, a more abundant supply of skilled labor does not strengthen the firms' bargaining power.

[Table 14 about here]

It is worth noting that the results should not be interpreted as that relaxing labor mobility restrictions hurt the welfare of labor—the result is only true when the overall mobility restriction is high and the relaxation is local[10]. With the high overall mobility restrictions, firms in the locally relaxed cities can benefit from the more abundant labor supply as labor can migrate in at low cost but cannot easily migrate out to other cities, even being exploited by the local firms. In other words, relaxed local hukou restrictions compensate the labor for the cost of firm monopsony and allow the firms to exercise pass-through. The channel does not work when the national labor market allows free mobility.

[10] Tombe and Zhu (2019) and Fang et al. (2023) both find significant labor mobility costs across the country despite the Hukou reforms in the recent years.

5.3 Alternative Labor Demand Channel: Bank Entry and Market Competition

Our interpretation of the positive relationship between bank concentration and the labor markdown is that firms pass financial burdens to their employees. Alternatively, one can also propose a competing channel: bank concentration impedes firm entry and thus increases incumbent firms' market power in the labor market. To rule out this alternative mechanism, we study how skill intensity affects the marginal effects of bank concentration on firm entry and compare the results with the labor markdown results (Table 10).

If the competition mechanism drives the positive coefficient in our baseline regressions, then the interaction between skill and bank HHI should have *opposite* signs for entry and labor markdown. The intuition is as follows. Suppose the interaction is negative for firm entry, so high-skill firms are less willing to enter cities with high bank concentration. Then those cities should have relatively less competitive labor demand by high-skill firms, and the labor markdown for high-skill firms should be higher. Then, the interaction between skill and bank HHI should be positive for labor markdown. The converse is true, respectively.

To test the hypothesis, we employ the firm registration database to construct variables on industry-specific firm dynamics. The State Administration for Industry and Commerce releases the firm registration database, which covers the universe of *all* registered firms—over 90 million in total—established in China since 1949. The firm registration data contains information on the firm's year of establishment, exit date (if applicable), 4-digit industry classification code, amount of registered capital, and the history of ownership changes (if any). We calculate the number of new entries in each city-industry-year cell and combine it with the previously constructed industry skill intensity and city-year bank concentration data. We examine the relationship between bank concentration and firm dynamics at the city-industry-year level by using the number of firm entries (in logs) as the dependent variable. Table 15 reports the regression results. The coefficient on the interaction between HHI and skill intensity is negative, indicating that skill-intensive firms are reluctant to enter cities with high bank concentration. This is probably because firms in high-skill-intensity industries find it hard to pass the cost to labor facing high financial frictions, and are thus less willing to enter the cities with high bank concentrations. Meanwhile, the same interaction term for the labor markdown regression in Table 10 is also negative, indicating that skill-intensive firms are less able to exploit employees when bank concentration rises. The two sets of regressions have *identical* signs for the coefficients on the interaction term, contradicting the prediction of the competition mechanism. Therefore, we rule out this alternative hypothesis.

[Table 15 about here]

6 Concluding Remarks

In this paper, we propose a novel channel with micro evidence through which the financial market frictions may transmit to labor market costs. Banks' market power enables them to charge higher rates at the cost of firms, but firms do not have to bear all the costs themselves. We find that firms can exploit their market powers in the labor market to pass the costs to the laborers— firms in cities with higher levels of bank concentration exhibit higher levels of labor markdown than those in low-concentration cities. The findings are robust to a number of robustness checks and alternative identification strategies, including DID and IV. We find that the pass-through is more salient among low-skill-intensity firms because low-skill labor has lower bargaining power in the labor market; it is more significant among Private-Owned-Enterprises (POEs) because State-Owned-Enterprises (SOEs) are less prone to financial frictions; and it is more so for larger firms because the larger firms have higher bargaining power in the labor market.

We further leverage the regional variations in the labor market conditions to investigate this pass-through channel. We find that the presence of labor protests and strong labor unions deter firms from passing the costs to their employees. Moreover, if a city relaxes its Hukou restrictions and thus attracts more labor into the local market, this more abundant labor supply will enable the firms to carry out more intense pass-through. We examine the relationship between firm entry and bank concentration to rule out the alternative story that the positive correlation between bank concentration and firm labor markdown is driven by the higher entry cost for firms, and thus a lack of competition among employers.

The mechanism bears significant implications for the influence of the financial market on the labor market. We provide micro-level evidence that financial frictions from bank concentration and the lack of bank competition affect firms' financial performance and, more importantly, may have a profound impact on the labor's welfare.

Understanding the mechanism of the pass-through yields important policy implications. Strong labor unions and a more integrated labor market may weaken the pass-through channel—however—the most fundamental reform lies in the liberalization of the banking sector. While we study the problem in the context of China during the period of bank liberalization, we believe that the mechanism elucidated herein may extend to broader contexts that feature bank concentration and weak labor protection. For example, the US has been witnessing a rising trend of banking sector concentration and a declining labor unionization rate in recent years, and thus, it may expect a strengthening linkage between the financial market frictions and the labor market costs.

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Figure 1: Evolution of bank branch HHI and total number of branches.

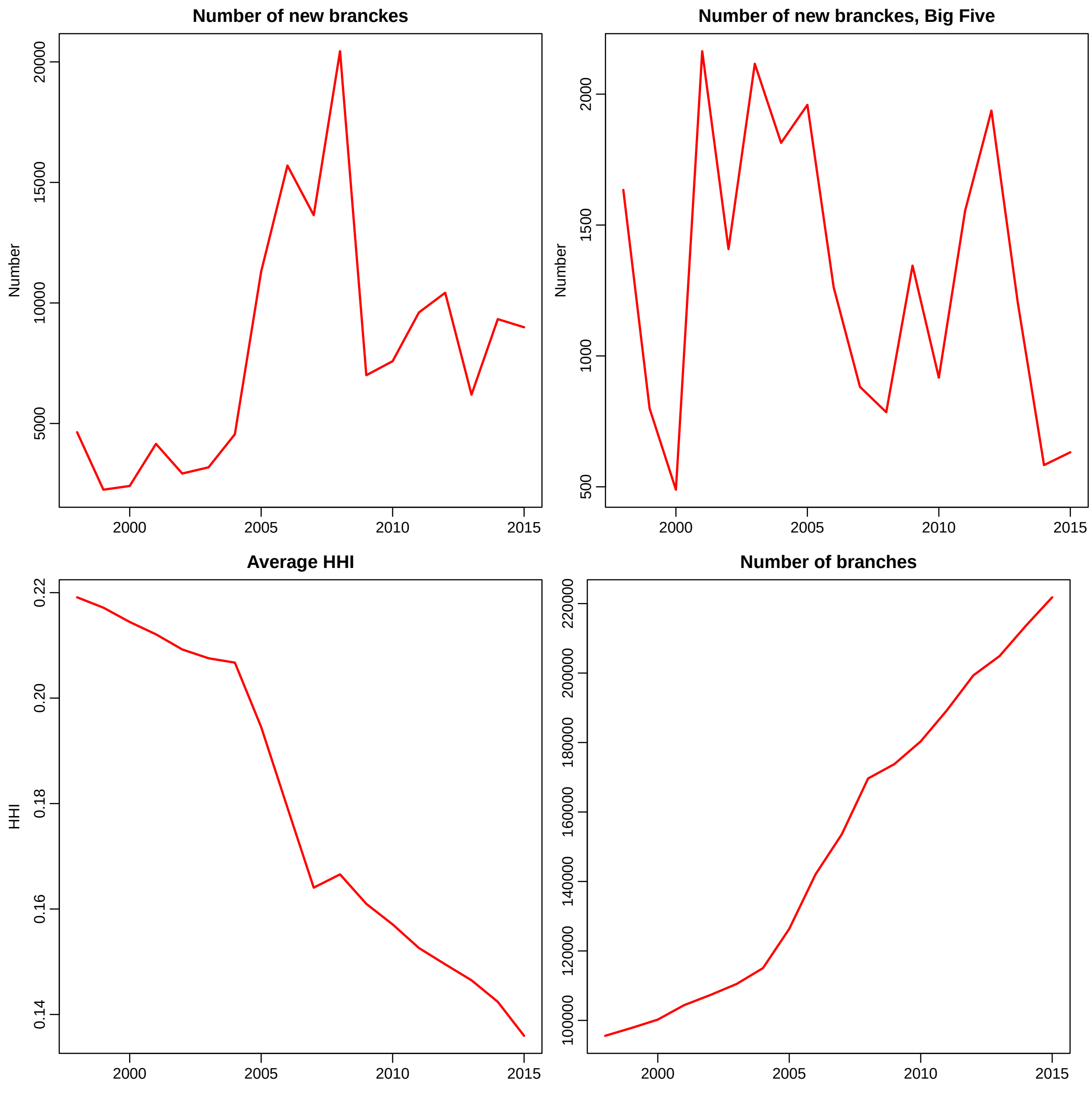
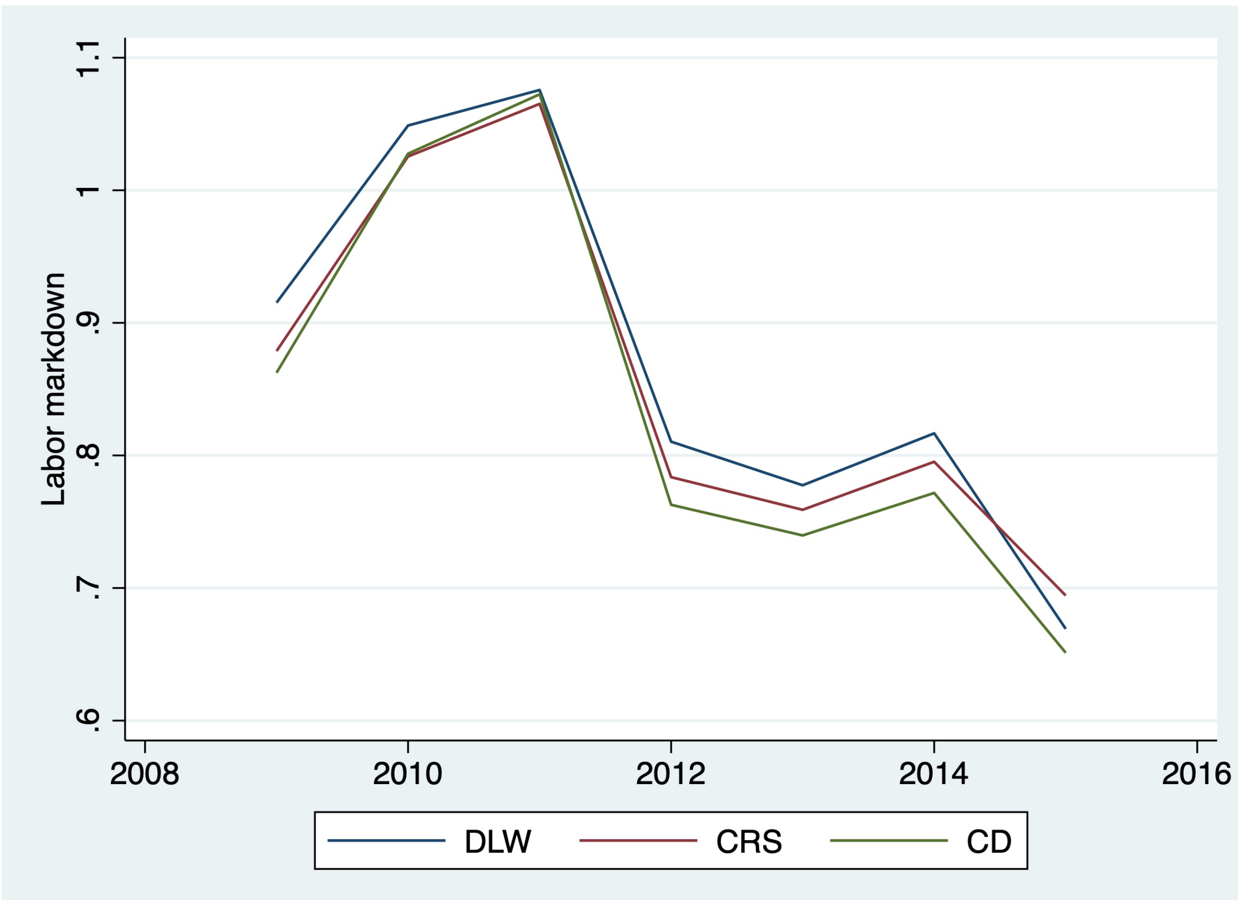
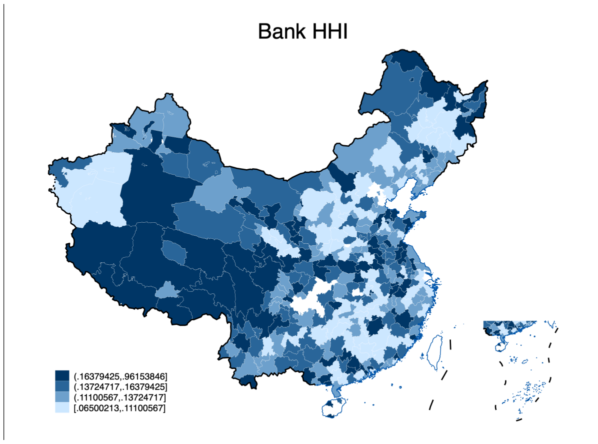


Figure 2: Evolution of labor markdowns in China.

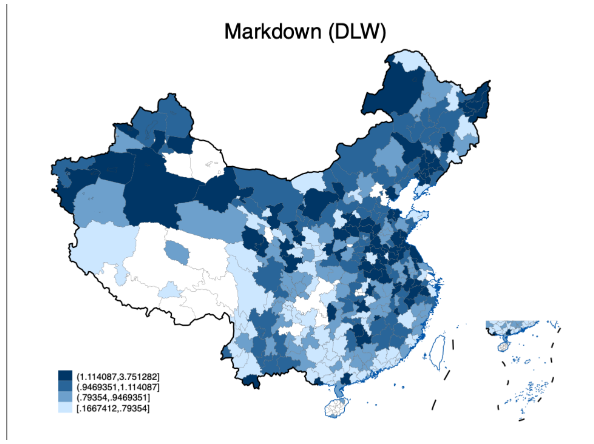


This figure plots the annual averages of our estimates of labor markdown. Our baseline measure is "DLW", but the three measures have similar values.

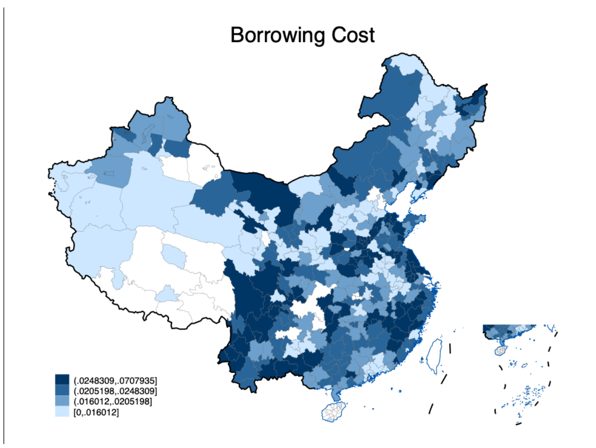
Figure 3: Geographical distribution of key variables. Each variable is averaged at the city level. White areas indicate missing observations.



(a) Geographical distribution of the bank branch HHI.



(b) Geographical distribution of the labor markdown.



(c) Geographical distribution of borrowing cost.

Table 1: HHI, Firm Financing Cost and Leverage

	Interest Rate		Leverage Ratio	
	POE	SOE	POE	SOE
	(1)	(2)	(3)	(4)
HHI	0.0213***	-0.0203	-0.184***	0.00711
	(0.00807)	(0.0252)	(0.00942)	(0.0454)
log(Asset)	-0.00226***	-0.000667	0.0102***	0.00929***
	(0.000209)	(0.000624)	(3.82e-05)	(0.000245)
Constant	0.0435***	0.0278***	0.119***	0.179***
	(0.00245)	(0.00794)	(0.000913)	(0.00471)
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Observations	263,620	22,948	23,138,547	457,671
R-squared	0.600	0.596	0.697	0.758

This table reports the results of estimating the relationship between bank concentration and firms' financial performance. For columns (1)-(2), the dependent variable is the firm's interest rate, defined as the ratio between a firm's annual interest payment and annual outstanding debt. The data sample includes all firms in the administrative tax data. For columns (1)-(2), the dependent variable is the firm's leverage ratio, defined as the ratio between a firm's outstanding debt and total equity. The data sample includes all firms in the SAIC registration database. Standard errors are clustered at the city-year level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 2: Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Firm-Year Level					
log(Output)	2410399	9.51	2.30	-1.10	22.27
log(Employment)	2410026	3.82	1.56	-1.11	33.00
log(Capital)	2279058	7.40	2.78	-3.99	19.65
log(Input)	2383028	9.27	2.35	-0.28	22.00
log(Reg. cap.)	2183117	6.27	2.09	-13.82	18.65
Interest rate	2410399	0.01	0.03	0.00	1.00
Product markup (DLW)	1136845	1.26	1.23	0.30	248.93
Product markup (CRS)	2383028	1.12	1.65	0.00	96.60
Product markup (CD)	2279058	1.12	1.36	0.00	55.58
Labor mardown (DLW)	1136845	10.69	31.22	0.00	473.47
Labor mardown (CRS)	2383028	18.13	59.19	0.00	3879.48
Labor mardown (CD)	2279058	12.61	39.13	0.03	10411.02
Panel B: City-Year Level					
HHI	2983	0.13	0.09	0.05	1
HHI (employment)	2983	0.16	0.12	0.03	1
# of bank branches	3002	586.46	545.64	0	5175
# of bank branches (big five)	3002	198.00	224.05	0	2012
# of bank branches (commercial)	3002	526.01	534.33	0	4990
# of bank branches (other)	3002	60.44	72.90	0	551
pop	2968	359.18	320.92	0.02	3392.11
GDP	2968	1729.35	2605.46	12.66	29887.02

This table presents the summary statistics for our main sample based on the administrative tax data. Panel A reports the summary statistics of the firm-year level variables. DLW: estimated using the method of De Loecker and Warzynski (2012). CRS: assuming constant returns to scale production functions. CD: assuming Cobb-Douglas production functions. Panel B corresponds to our key independent variable—bank HHI—at city-year level. Panel C reports the correlation between key variables

Table 3: Baseline regression: Financial Friction and Labor Markdown

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	0.931**	0.0628	0.620***	-0.163	0.527**	-0.114
	(0.371)	(0.149)	(0.233)	(0.153)	(0.204)	(0.164)
L.Markup	-0.000234		0.00790**		-0.0288***	
	(0.00652)		(0.00371)		(0.00407)	
log(Population)	-0.0391**	0.0197*	-0.0269*	0.0348***	-0.0157	0.0271*
	(0.0179)	(0.0115)	(0.0151)	(0.0127)	(0.0137)	(0.0141)
log(GDP)	-0.0883*	-0.0190	-0.0629*	0.00623	-0.0411	-0.0391
	(0.0519)	(0.0213)	(0.0343)	(0.0248)	(0.0287)	(0.0311)
K	-0.0100**	0.00720***	-0.0247***	0.0173***	0.0125***	-0.0255***
	(0.00442)	(0.00158)	(0.00338)	(0.00150)	(0.00267)	(0.00156)
L	-0.545***	0.0578***	-0.584***	0.0999***	-0.510***	0.0217***
	(0.00959)	(0.00329)	(0.00693)	(0.00328)	(0.00658)	(0.00326)
M	0.638***	-0.140***	0.677***	-0.174***	0.492***	0.0247***
	(0.00773)	(0.00456)	(0.00636)	(0.00595)	(0.00600)	(0.00624)
Constant	-4.263***	1.245***	-4.788***	0.774***	-3.547***	-0.00586
	(0.441)	(0.200)	(0.292)	(0.196)	(0.248)	(0.237)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,266	797,666	740,725	1,527,289	723,478	1,484,190
R-squared	0.898	0.587	0.903	0.580	0.891	0.471

This table reports the results of estimating Equation (5). The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice. The dependent variable for all columns is the DLW labor markdown, where it is estimated using the method of De Loecker and Warzynski (2012). HHI is based on the branch share of each bank in each city. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 4: Robustness: Measuring HHI by Employment Size

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI (employment)	0.868***	-0.0561	0.828***	-0.0846	0.808***	-0.00153
	(0.185)	(0.0505)	(0.181)	(0.0772)	(0.189)	(0.00497)
Markup	-0.0934***		0.0880***		3.180***	
	(0.00742)		(0.00475)		(0.0770)	
K	0.0215***	-0.0105***	0.0165***	-0.0126***	-0.0137***	0.00168***
	(0.00260)	(0.000710)	(0.00255)	(0.00109)	(0.00266)	(7.00e-05)
L	-0.447***	0.0107***	-0.491***	0.0524***	-0.513***	0.00761***
	(0.00416)	(0.00114)	(0.00408)	(0.00174)	(0.00429)	(0.000112)
M	0.361***	-0.0822***	0.367***	-0.135***	0.452***	-0.0187***
	(0.00184)	(0.000473)	(0.00181)	(0.000723)	(0.00228)	(4.66e-05)
Constant	-0.900***	1.518***	-0.892***	2.370***	-1.432***	0.184***
	(0.0409)	(0.0107)	(0.0401)	(0.0164)	(0.0426)	(0.00106)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359,186	359,186	359,186	359,186	359,186	359,186
R-squared	0.816	0.631	0.822	0.604	0.827	0.728

This table reports the results of estimating Equation (5). The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. HHI (employment) is based on the employment share of each bank in each city. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 5: Instrumental Variable Approach

	(1)	(2)	(3)
HHI neighbor	1.555***		1.554***
	(0.00357)		(0.00356)
Financial/fiscal experience		0.00214***	0.00173***
		(8.39e-05)	(6.21e-05)
Markup	-0.000188***	-8.06e-05	-0.000195***
	(6.78e-05)	(9.12e-05)	(6.77e-05)
K	-6.45e-05***	-0.000108***	-6.66e-05***
	(2.38e-05)	(3.20e-05)	(2.37e-05)
L	-2.77e-05	2.67e-05	-2.86e-05
	(3.76e-05)	(5.06e-05)	(3.75e-05)
M	-1.04e-05	6.28e-05***	-8.25e-06
	(1.68e-05)	(2.26e-05)	(1.68e-05)
Constant	-0.0672***	0.107***	-0.0673***
	(0.000499)	(0.000401)	(0.000498)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes
Observations	335,883	337,811	335,883
R-squared	0.980	0.963	0.980

This table reports the results of estimating the first stage of the IV regression. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the HHI in the local market. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 6: Instrumental Variable Approach

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	4.692*	0.300	2.138**	-2.098	2.137**	0.300
	(2.830)	(0.663)	(0.909)	(1.413)	(0.881)	(0.663)
L.Markup	0.00401		0.00898**		-0.0285***	
	(0.00634)		(0.00396)		(0.00415)	
log(Population)	-0.0337*	0.0180	-0.0232	0.0222	-0.0126	0.0180
	(0.0190)	(0.0115)	(0.0157)	(0.0139)	(0.0144)	(0.0115)
log(GDP)	-0.0809	-0.00814	-0.0485	0.0211	-0.0268	-0.00814
	(0.0515)	(0.0203)	(0.0336)	(0.0234)	(0.0287)	(0.0203)
K	-0.00950**	0.00676***	-0.0253***	0.0167***	0.0126***	0.00676***
	(0.00450)	(0.00158)	(0.00348)	(0.00157)	(0.00274)	(0.00158)
L	-0.556***	0.0571***	-0.594***	0.0998***	-0.520***	0.0571***
	(0.00834)	(0.00327)	(0.00630)	(0.00348)	(0.00606)	(0.00327)
M	0.645***	-0.139***	0.683***	-0.174***	0.498***	-0.139***
	(0.00796)	(0.00454)	(0.00635)	(0.00601)	(0.00623)	(0.00454)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	397,527	738,692	691,184	1,405,176	674,342	738,692
R-squared	0.555	0.161	0.602	0.215	0.502	0.161

This table reports the results of estimating Equation (5). The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. HHI (employment) is based on the employment share of each bank in each city. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 7: Difference-in-Differences: Bank Deregulation and Labor Markdown

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
log(# of Banks 2008)*Post	0.378**	-0.0105	0.353**	0.0401**	0.302*	0.0690***
	(0139)	(0.0300)	(0.173)	(0.0178)	(0.162)	(0.0261)
L.Markup	-0.000298		0.00780**		-0.0288***	
	(0.00654)		(0.00372)		(0.00408)	
log(Population)	-0.0428**	0.0196*	-0.0312**	0.0338***	-0.0194	0.0248*
	(0.0181)	(0.0115)	(0.0153)	(0.0127)	(0.0140)	(0.0142)
log(GDP)	-0.104*	-0.0187	-0.0826**	0.0138	-0.0584*	-0.0270
	(0.0564)	(0.0220)	(0.0385)	(0.0234)	(0.0319)	(0.0283)
K	-0.0100**	0.00720***	-0.0247***	0.0175***	0.0125***	-0.0252***
	(0.00443)	(0.00158)	(0.00339)	(0.00150)	(0.00267)	(0.00154)
L	-0.546***	0.0578***	-0.585***	0.0998***	-0.511***	0.0214***
	(0.00960)	(0.00330)	(0.00694)	(0.00330)	(0.00658)	(0.00332)
M	0.638***	-0.140***	0.677***	-0.174***	0.492***	0.0244***
	(0.00773)	(0.00456)	(0.00636)	(0.00590)	(0.00600)	(0.00610)
Constant	-6.495***	1.319***	-6.863***	0.464**	-5.321***	-0.512*
	(1.326)	(0.206)	(1.078)	(0.215)	(1.005)	(0.272)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,266	797,666	740,725	1,527,289	723,478	1,484,190
R-squared	0.898	0.587	0.903	0.580	0.891	0.472

This table reports the results of estimating the DID model. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Log of the number of commercial banks' branches in year 2008 (the year before the reform) is the measure for treatment intensity—the more branches there were before the reform, the lower the treatment intensity is; and year 2009 is the treatment starting year. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 8: Heterogeneity: SOE vs. POE

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	1.022***	0.0747	0.734***	-0.127	0.638***	-0.0919
	(0.386)	(0.144)	(0.237)	(0.155)	(0.208)	(0.165)
L.Markup	-0.000261		0.00786**		-0.0288***	
	(0.00652)		(0.00371)		(0.00407)	
HHI*SOE	-0.810*	-0.122	-1.182***	-0.364	-1.176***	-0.223
	(0.429)	(0.209)	(0.296)	(0.235)	(0.272)	(0.241)
log(Population)	-0.0393**	0.0197*	-0.0269*	0.0348***	-0.0156	0.0272*
	(0.0179)	(0.0115)	(0.0151)	(0.0127)	(0.0138)	(0.0141)
log(GDP)	-0.0892*	-0.0192	-0.0649*	0.00570	-0.0431	-0.0395
	(0.0520)	(0.0213)	(0.0345)	(0.0248)	(0.0288)	(0.0312)
K	-0.0100**	0.00720***	-0.0247***	0.0173***	0.0125***	-0.0255***
	(0.00442)	(0.00158)	(0.00339)	(0.00150)	(0.00267)	(0.00156)
L	-0.545***	0.0578***	-0.584***	0.0999***	-0.510***	0.0217***
	(0.00960)	(0.00329)	(0.00693)	(0.00328)	(0.00658)	(0.00326)
M	0.638***	-0.140***	0.677***	-0.174***	0.492***	0.0247***
	(0.00773)	(0.00456)	(0.00636)	(0.00595)	(0.00600)	(0.00624)
Constant	-4.255***	1.247***	-4.772***	0.778***	-3.530***	-0.00366
	(0.442)	(0.200)	(0.293)	(0.197)	(0.249)	(0.238)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,266	797,666	740,725	1,527,289	723,478	1,484,190
R-squared	0.898	0.587	0.903	0.580	0.891	0.471

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and a dummy variable taking value 1 for SOEs. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 9: Heterogeneity: Firm Size Strengthens Pass Through

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	-0.504	1.243***	-0.632	1.955***	-0.295	1.839***
	(1.040)	(0.346)	(0.604)	(0.429)	(0.497)	(0.432)
L.Markup	-0.00174		0.00674*		-0.0284***	
	(0.00646)		(0.00364)		(0.00406)	
HHI*log(Reg. cap.)	0.199*	-0.168***	0.179**	-0.316***	0.117**	-0.291***
	(0.120)	(0.0422)	(0.0712)	(0.0586)	(0.0583)	(0.0622)
log(Population)	-0.0362**	0.0210*	-0.0245	0.0341***	-0.0132	0.0270*
	(0.0181)	(0.0117)	(0.0154)	(0.0129)	(0.0139)	(0.0142)
log(GDP)	-0.0893*	-0.0217	-0.0669*	0.00176	-0.0435	-0.0453
	(0.0516)	(0.0216)	(0.0343)	(0.0255)	(0.0289)	(0.0321)
K	-0.0103**	0.00686***	-0.0250***	0.0173***	0.0122***	-0.0259***
	(0.00449)	(0.00160)	(0.00345)	(0.00150)	(0.00280)	(0.00159)
L	-0.548***	0.0574***	-0.585***	0.0993***	-0.512***	0.0213***
	(0.00977)	(0.00321)	(0.00706)	(0.00333)	(0.00672)	(0.00333)
M	0.638***	-0.140***	0.676***	-0.174***	0.492***	0.0241***
	(0.00777)	(0.00460)	(0.00638)	(0.00601)	(0.00606)	(0.00631)
Constant	-4.249***	1.255***	-4.749***	0.808***	-3.533***	0.0489
	(0.439)	(0.203)	(0.293)	(0.201)	(0.250)	(0.244)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	402,409	749,398	696,907	1,416,832	681,544	1,379,035
R-squared	0.898	0.583	0.903	0.576	0.892	0.466

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and the firms' registered capital. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 10: Heterogeneity: Skill Mitigates Pass Through

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	1.055***	0.111	0.709***	-0.115	0.632***	-0.121
	(0.376)	(0.147)	(0.231)	(0.153)	(0.204)	(0.165)
L.Markup	-0.000331		0.00788**		-0.0288***	
	(0.00652)		(0.00371)		(0.00407)	
HHI*High skill	-0.813*	-0.286	-0.575*	-0.238	-0.687**	0.0344
	(0.492)	(0.190)	(0.346)	(0.218)	(0.323)	(0.241)
log(Population)	-0.0393**	0.0196*	-0.0270*	0.0347***	-0.0157	0.0271*
	(0.0179)	(0.0115)	(0.0151)	(0.0127)	(0.0137)	(0.0140)
log(GDP)	-0.0894*	-0.0195	-0.0639*	0.00591	-0.0422	-0.0391
	(0.0520)	(0.0213)	(0.0344)	(0.0248)	(0.0287)	(0.0312)
K	-0.0101**	0.00719***	-0.0247***	0.0173***	0.0125***	-0.0255***
	(0.00439)	(0.00158)	(0.00337)	(0.00150)	(0.00266)	(0.00156)
L	-0.546***	0.0577***	-0.585***	0.0999***	-0.511***	0.0217***
	(0.00960)	(0.00329)	(0.00694)	(0.00327)	(0.00658)	(0.00326)
M	0.638***	-0.140***	0.677***	-0.174***	0.492***	0.0247***
	(0.00773)	(0.00456)	(0.00635)	(0.00595)	(0.00600)	(0.00624)
Constant	-4.247***	1.252***	-4.776***	0.779***	-3.533***	-0.00653
	(0.442)	(0.200)	(0.292)	(0.197)	(0.248)	(0.238)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,266	797,666	740,725	1,527,289	723,478	1,484,190
R-squared	0.898	0.587	0.903	0.580	0.891	0.471

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and an industry-level skill intensity measure. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 11: Labor Protests Mitigate Pass Through

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	1.105*	0.444	0.867	0.388	0.733	0.438
	(0.587)	(0.275)	(0.624)	(0.301)	(0.548)	(0.291)
L.Markup	0.00842		0.0171***		-0.0431***	
	(0.00812)		(0.00633)		(0.00856)	
Protest	0.0239	0.000452	0.0475	-0.0135	0.0380	0.000981
	(0.0392)	(0.0229)	(0.0380)	(0.0247)	(0.0353)	(0.0229)
HHI*Protest	-0.584*	-0.0284	-0.765*	0.0898	-0.649	-0.102
	(0.291)	(0.220)	(0.433)	(0.239)	(0.401)	(0.214)
log(Population)	-0.0282	0.0316***	-0.0218	0.0314***	-0.0167	0.0241***
	(0.0178)	(0.00855)	(0.0157)	(0.00939)	(0.0145)	(0.00876)
log(GDP)	-0.107	0.0628**	-0.120*	0.0804***	-0.0995*	0.0535**
	(0.0671)	(0.0281)	(0.0636)	(0.0290)	(0.0538)	(0.0236)
K	-0.00761	0.00335	-0.0211***	0.0155***	0.0125***	-0.0186***
	(0.00614)	(0.00206)	(0.00555)	(0.00213)	(0.00473)	(0.00234)
L	-0.527***	0.0462***	-0.560***	0.0891***	-0.489***	0.0166***
	(0.0140)	(0.00443)	(0.0123)	(0.00434)	(0.0116)	(0.00389)
M	0.643***	-0.155***	0.681***	-0.213***	0.492***	-0.0101
	(0.0104)	(0.00675)	(0.0100)	(0.00788)	(0.00935)	(0.00675)
Constant	-4.423***	0.774***	-4.672***	0.688***	-3.255***	-0.436*
	(0.565)	(0.250)	(0.536)	(0.265)	(0.457)	(0.229)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	261,003	382,236	356,269	537,629	347,549	517,841
R-squared	0.904	0.635	0.913	0.681	0.902	0.555

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and the firms' industries' skill intensity. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively. This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and a city-level protest measure. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 12: Labor Unions Mitigate Pass Through

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	7.634***	-3.883***	5.105***	-5.564***	3.020*	-4.733*
	(2.856)	(1.457)	(1.856)	(1.979)	(1.568)	(2.616)
L.Markup	-0.000182		0.00796**		-0.0289***	
	(0.00650)		(0.00371)		(0.00406)	
log(Union)	0.133*	-0.0577	0.0378	-0.128**	-0.000545	-0.183***
	(0.0793)	(0.0387)	(0.0486)	(0.0538)	(0.0421)	(0.0672)
HHI*log(Union)	-0.648**	0.387***	-0.441**	0.537***	-0.245*	0.458*
	(0.262)	(0.141)	(0.176)	(0.194)	(0.149)	(0.257)
log(Population)	0.0308	0.000721	-0.0334	-0.0392	-0.0410	-0.111*
	(0.0683)	(0.0367)	(0.0420)	(0.0497)	(0.0370)	(0.0583)
log(GDP)	-0.0732	-0.0287	-0.0542	-0.0123	-0.0384	-0.0615*
	(0.0485)	(0.0218)	(0.0335)	(0.0268)	(0.0282)	(0.0354)
K	-0.0102**	0.00726***	-0.0248***	0.0174***	0.0125***	-0.0253***
	(0.00440)	(0.00155)	(0.00337)	(0.00148)	(0.00266)	(0.00153)
L	-0.545***	0.0576***	-0.584***	0.0998***	-0.510***	0.0216***
	(0.00960)	(0.00326)	(0.00694)	(0.00326)	(0.00658)	(0.00326)
M	0.638***	-0.140***	0.677***	-0.174***	0.492***	0.0249***
	(0.00773)	(0.00455)	(0.00635)	(0.00594)	(0.00600)	(0.00623)
Constant	-6.172***	2.022***	-5.200***	2.658***	-3.407***	2.854**
	(1.196)	(0.647)	(0.802)	(0.910)	(0.681)	(1.135)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,266	797,666	740,725	1,527,289	723,478	1,484,190
R-squared	0.898	0.587	0.903	0.580	0.891	0.472

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and a firm-level measure of the registration capital. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 13: Channel: Labor Mobility Strengthens Pass Through

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	0.887**	0.0832	0.594**	-0.140	0.505**	-0.0966
	(0.368)	(0.148)	(0.231)	(0.152)	(0.202)	(0.162)
L.Markup	-0.000302		0.00794**		-0.0286***	
	(0.00651)		(0.00371)		(0.00408)	
Hukou	-0.0622***	0.0328***	-0.0505**	0.0263	-0.0435*	0.0185
	(0.0240)	(0.0113)	(0.0243)	(0.0216)	(0.0229)	(0.0275)
HHI*Hukou	0.611***	-0.0145	0.550***	0.0144	0.487***	0.0341
	(0.0895)	(0.0373)	(0.0939)	(0.0700)	(0.0883)	(0.0857)
log(Population)	-0.0384**	0.0204*	-0.0261*	0.0352***	-0.0149	0.0275**
	(0.0180)	(0.0115)	(0.0151)	(0.0126)	(0.0138)	(0.0140)
log(GDP)	-0.0878*	-0.0183	-0.0611*	0.00488	-0.0394	-0.0401
	(0.0519)	(0.0212)	(0.0341)	(0.0248)	(0.0286)	(0.0312)
K	-0.0100**	0.00724***	-0.0247***	0.0173***	0.0125***	-0.0255***
	(0.00444)	(0.00158)	(0.00339)	(0.00150)	(0.00268)	(0.00157)
L	-0.545***	0.0578***	-0.584***	0.0999***	-0.510***	0.0216***
	(0.00959)	(0.00329)	(0.00693)	(0.00327)	(0.00658)	(0.00325)
M	0.638***	-0.140***	0.677***	-0.174***	0.492***	0.0247***
	(0.00773)	(0.00456)	(0.00635)	(0.00595)	(0.00600)	(0.00624)
Constant	-4.268***	1.224***	-4.808***	0.772***	-3.566***	-0.00838
	(0.444)	(0.200)	(0.292)	(0.198)	(0.249)	(0.239)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,266	797,666	740,725	1,527,289	723,478	1,484,190
R-squared	0.898	0.587	0.903	0.580	0.891	0.471

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and a dummy variable taking value 1 for cities who has already relaxed its hukou restrictions. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 14: Channel: Labor Mobility Strengthens Pass Through

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	0.969**	0.169	0.619***	0.0118	0.556***	0.0710
	(0.379)	(0.153)	(0.225)	(0.167)	(0.199)	(0.169)
L.Markup	-0.000248		0.00792**		-0.0288***	
	(0.00651)		(0.00370)		(0.00406)	
Hukou (skill)	0.0159	0.0576*	0.00496	0.105***	0.0177	0.107***
	(0.0604)	(0.0321)	(0.0374)	(0.0361)	(0.0329)	(0.0393)
HHI*Hukou (skill)	-0.131	-0.399	0.0165	-0.782***	-0.101	-0.849***
	(0.530)	(0.256)	(0.320)	(0.280)	(0.281)	(0.321)
log(Population)	-0.0394**	0.0178	-0.0270*	0.0301**	-0.0162	0.0223
	(0.0179)	(0.0117)	(0.0150)	(0.0130)	(0.0137)	(0.0143)
log(GDP)	-0.0881*	-0.0177	-0.0631*	0.00910	-0.0409	-0.0359
	(0.0515)	(0.0211)	(0.0341)	(0.0244)	(0.0285)	(0.0308)
K	-0.0100**	0.00720***	-0.0247***	0.0173***	0.0125***	-0.0255***
	(0.00443)	(0.00158)	(0.00339)	(0.00150)	(0.00268)	(0.00156)
L	-0.545***	0.0577***	-0.584***	0.0998***	-0.510***	0.0215***
	(0.00960)	(0.00330)	(0.00694)	(0.00328)	(0.00658)	(0.00327)
M	0.638***	-0.140***	0.677***	-0.174***	0.492***	0.0246***
	(0.00773)	(0.00456)	(0.00636)	(0.00595)	(0.00600)	(0.00623)
Constant	-4.268***	1.228***	-4.790***	0.751***	-3.552***	-0.0296
	(0.433)	(0.199)	(0.290)	(0.196)	(0.246)	(0.238)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424,266	797,666	740,725	1,527,289	723,478	1,484,190
R-squared	0.898	0.587	0.903	0.580	0.891	0.471

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and the firms' industries' skill intensity. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the labor markdown and product markup, where —DLW: estimated using the method of De Loecker and Warzynski (2012); CRS: assuming constant returns to scale production functions; CD: assuming Cobb-Douglas production functions. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 15: Alternative: Firm Entry

	(1)	(2)
HHI	0.149	-0.0657
	(0.0940)	(0.121)
HHI*Skill	-1.355***	-2.296***
	(0.188)	(0.270)
Constant	7.312***	7.480***
	(0.0173)	(0.0158)
City FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Province*Year FE	No	Yes
Observations	438,636	394,518
R-squared	0.511	0.516

This table reports the results of estimating Equation (5) with one more term—the interaction between bank HHI and the incumbent firms' industries' skill intensity. The unit of observation is firm-year, and the data sample covers the period between 2008 to 2015 and all firms that appeared at least twice in the administrative tax record database. The dependent variable for all columns is the log number of firm entries. Standard errors are clustered at the province level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Online Appendix A: Tables

Figure A1: Event Study of Difference-in-differences Test on Bank Expansion

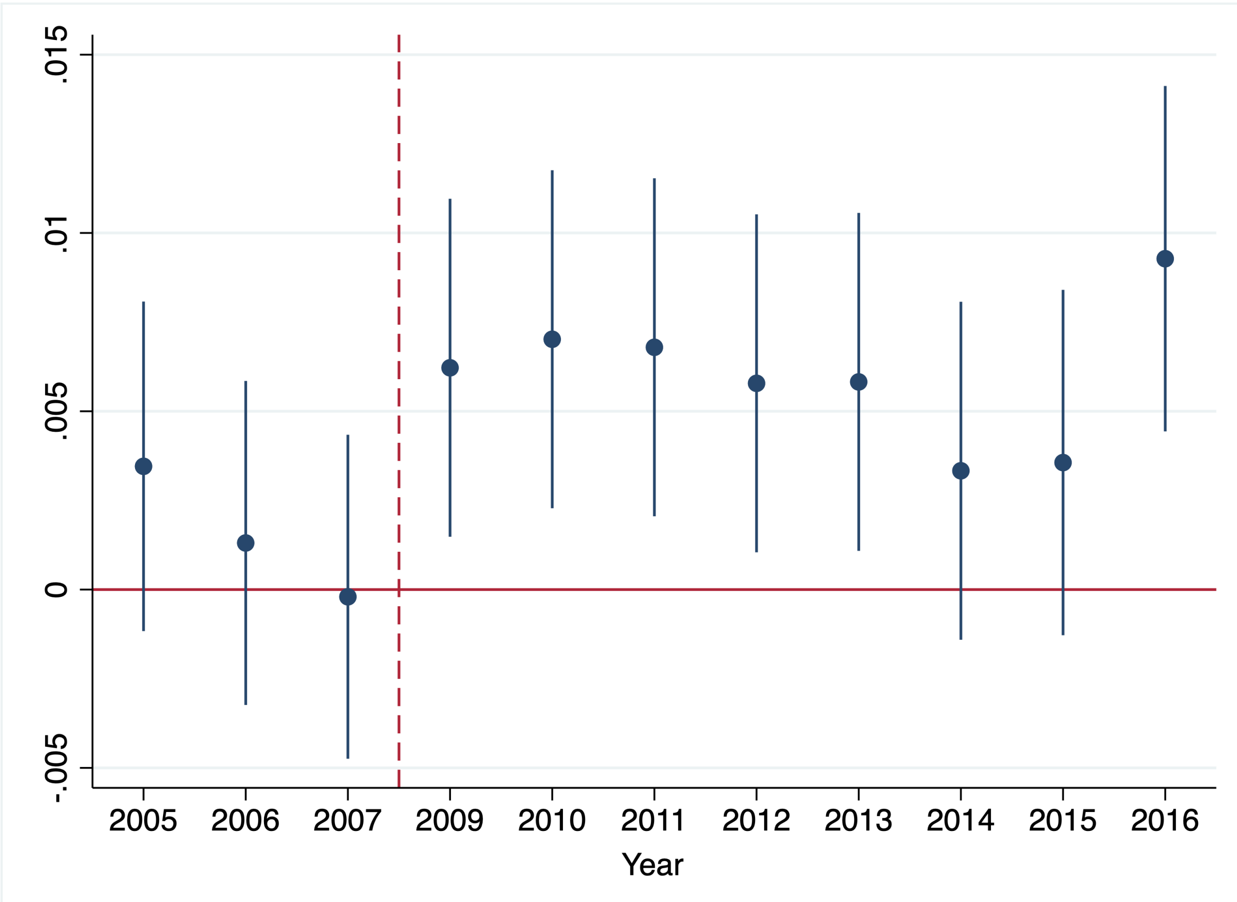


Table A1: Robustness: Manufacturing Firms Only

	DLW		CD		CRS	
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5) Markdown	(6) Markup
HHI	0.829**	0.0543	0.523**	-0.205	0.441**	-0.136
	(0.369)	(0.154)	(0.218)	(0.169)	(0.193)	(0.179)
L.Markup	-0.00224		0.00405		-0.0304***	
	(0.00726)		(0.00433)		(0.00420)	
log(Population)	-0.0414**	0.0203*	-0.0244	0.0335***	-0.0143	0.0277**
	(0.0204)	(0.0115)	(0.0168)	(0.0121)	(0.0152)	(0.0134)
log(GDP)	-0.0951*	-0.0476*	-0.0691*	-0.0201	-0.0493	-0.0599*
	(0.0567)	(0.0253)	(0.0375)	(0.0261)	(0.0322)	(0.0343)
K	-0.0113***	0.00628***	-0.0254***	0.0189***	0.0104***	-0.0270***
	(0.00311)	(0.00170)	(0.00251)	(0.00162)	(0.00207)	(0.00175)
L	-0.527***	0.0626***	-0.565***	0.109***	-0.486***	0.0221***
	(0.0100)	(0.00342)	(0.00753)	(0.00435)	(0.00681)	(0.00449)
M	0.607***	-0.134***	0.644***	-0.167***	0.456***	0.0381***
	(0.00873)	(0.00427)	(0.00675)	(0.00734)	(0.00588)	(0.00785)
Constant	-3.949***	1.354***	-4.509***	0.837***	-3.259***	0.0383
	(0.483)	(0.222)	(0.317)	(0.208)	(0.275)	(0.261)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	322,739	573,165	539,004	1,018,011	529,737	995,605
R-squared	0.879	0.555	0.880	0.543	0.865	0.443

Table A2: Summary statistics for ASIF data.

	Panel A: Firm-Year Level				
	Obs	Mean	Std.Dev.	Min.	Max.
Y	1182929	887.97	6880.56	0.02	1230551.62
M	1182929	648.20	5155.98	0.01	849708.75
K	1182929	305.66	3360.93	0.01	753064.50
L	1182929	294.73	1027.54	10.00	166857.06
Labor markdown (DLW)	1180904	7.05	43.81	0.00	36484
Labor markdown (CRS)	1180904	7.39	43.44	0.30	36628
Labor markdown (CD)	1180904	8.06	49.91	0.00	42086
Product markup (DLW)	1182929	1.27	0.20	0.64	4.41
Product markup (CRS)	1182929	1.13	0.19	0.01	4.13
Product markup (CD)	1182929	1.13	0.19	0.84	31
Panel B: City-Year Level					
HHI	2799	0.20	0.16	0.04	1.00
HHI (employment)	3082	0.25	0.14	0.08	1.00
# of bank branches	2816	340.73	334.32	0.00	3643.00
# of bank branches (big five)	2816	167.03	190.10	0.00	1749.00
# of bank branches (commercial)	2816	301.86	319.34	0.00	3560.00
# of bank branches (other)	2816	38.87	53.33	0.00	544.00

Panel C: Correlations

	HHI	Labor markdown (DLW)	Product markup (DLW)
HHI	1	0.02	-0.01
Labor markdown (DLW)		1	-0.06
Product markup (DLW)			1

DLW: estimated using the method of De Loecker and Warzynski (2012). CRS: assuming constant returns to scale production functions. CD: assuming Cobb-Douglas production functions.

Table A3: Robustness: Baseline Regressions Using ASIF Data.

	DLW		CD		
	(1) Markdown	(2) Markup	(3) Markdown	(4) Markup	(5 Mark
HHI	0.117**	−0.0206*	0.121**	−0.0169*	0
	(2.83)	(−2.23)	(2.97)	(−2.13)	(2
markup_{t-1}	−0.0229***	−0.0194***	0.0228**	−0.0425***	−0
	(−3.49)	(−13.16)	(3.17)	(−30.30)	(−10
k	−0.0337***	0.000791*	−0.0421***	0.0115***	−0
	(−19.78)	(2.07)	(−25.01)	(34.99)	(−4
l	−0.657***	0.0115***	−0.674***	0.0415***	−0
	(−239.38)	(18.67)	(−248.87)	(78.62)	(−252
m	0.716***	−0.0290***	0.744***	−0.0825***	0
	(333.48)	(−60.38)	(351.76)	(−199.95)	(333
Constant	0.610***	1.398***	0.527***	1.364***	0
	(35.41)	(361.98)	(30.70)	(407.21)	(46
Observations	660573	661355	660573	661355	660573
R^2	0.86	0.71	0.86	0.67	0
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Ye*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Ye*
Province-by-Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Ye*

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: First-stage regression of DID.

	(1)	(2)
log(n# of Banks 2008)*Post	0.00526***	0.00213*
	(0.00111)	(0.00127)
Constant	0.136***	0.149***
	(0.00432)	(0.00492)
City FE	Yes	Yes
Year FE	Yes	Yes
Province-by-Year FE	No	Yes
Observations	4,183	4,147
R-squared	0.949	0.959