Minimum Wage and Corporate Investment

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Abstract

This paper studies the effects of minimum wages (MWs) on corporate investment decisions using census data of Chinese manufacturing firms over the 1998-2008 period. In China, MW policies vary across more than 2,800 counties. We exploit the MW policy discontinuities at county borders and explore how MWs affect firms located around shared borders of any two adjacent counties that are subject to different MWs. We find that corporate investments increase as a result of MW hikes. The effect is stronger for firms that are labor-intensive, that cannot sufficiently pass labor cost on to consumers, that have better access to finance, and that are located in regions with better contract enforcement. Our findings are explained by a capital-labor substitution hypothesis: firms make more investments in fixed assets and adopt new technologies to offset growing labor costs caused by the higher wage floor. We also document a positive effect of MWs on long-term debts, suggesting the increase in investment is externally financed.

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"The introduction of new techniques by the entrepreneurs is the more common source of increased labor productivity (caused by minimum wage legislation)."

George J. Stigler (1946)

1 Introduction

As a core element of labor policies and a controversial issue in the political arena, minimum wage (MW) policy has received much attention in the economics literature. The long-standing and still heated debates over MW provision mainly focus on whether it eliminates poverty, reduces inequality, depresses firm employment incentives, etc.[1] However, little is known about how and to what extent MW policy shapes firm-level policies.

In this study, we estimate the firm-level impact of MW hikes on corporate investment decisions. Theoretically, the investment effects of MW are ambiguous. A higher wage floor may induce capital-labor substitution, given that capital and labor are substitutes. As MW hikes drive up the price of labor relative to capital, firms tend to shift toward a high capital-intensity business model that is less reliant on labor. In particular, firms can adopt technologies that will replace MW-earning labor in routine tasks (e.g., Autor *et al.* (2003); Acemoglu and Restrepo (2017)). This capital-labor substitution effect implies a positive influence of MW on firm investment, which is consistent with empirical findings suggesting a negative impact of MW hikes on firm employment (Jardim *et al.* (2017); Meer and West (2016); Sorkin (2015)), and survey results showing that employers' main aim following MW hikes is to raise productivity. [2] Anecdotal evidence suggests that McDonald's, in response to the "Fight for $15" MW campaign, is rolling out a new scheme to replace full-service employees with self-service alternatives. [3]

Other theories, in contrast, suggest MW hikes may lead to a *decline* in corporate investments. Higher operating costs reduce potential future cash flows and thus make investment projects less attractive. In addition, an increased wage share of operating costs caused by MW hikes makes firms riskier because they have less flexibility to adjust their operating costs to cope with economic recessions (Fazzari *et al.* (1988); Lin *et al.* (2017)). Taken

[1] See Neumark and Wascher (2008), and Card and Krueger (2015) for reviews, Aaronson, Agarwal, and French (2012), MaCurdy (2015), and Jardim et al. (2017) for recent discussions.

[2] A survey of 1,037 U.K. employers conducted by the Chartered Institute of Personnel and Development (CIPD) and Resolution Foundation in 2015 finds about 30% of surveyed employers indicate that their primary focus following MW hikes is to raise productivity by investing in training and equipment. See survey report at `https://www.cipd.co.uk/Images/weighing-up-the-wage-floor_2016-employer-responses-national-living-wage_tcm18-10963.pdf`

[3] See `https://www.forbes.com/sites/realspin/2016/11/29/thanks-to-fight-for-15-minimum-wage-mcdonalds-unveils-job-replacing-self-service-kiosks-nationwide/23efb8834fbc`.

together, lower future cash flows and higher distress risk caused by MW hikes may lead firms to forgo investment projects they would have otherwise launched. As theories provide mixed guidance, how MW affects corporate investment behavior is therefore an unanswered empirical question.

Despite its importance, few studies have addressed this question, in part due to the severe empirical challenges in estimating the treatment effects of MWs. The MW data used in previous studies present limited cross-sectional variation, as in most countries MW policies vary at the level of broad geographical areas such as a country/state. Other economic variables that vary at an equivalent geographical level may confound the treatment effects of MW.[4] In addition, private firms, particularly small and medium businesses, are more exposed to MW shocks because they tend to be less technologically intensive and have a greater marginal return through investing in technology than their publicly traded counterparts. However, due to the limited availability of financial data for private firms, other studies use publicly traded firms to evaluate the impact of MW. For example, two contemporaneous papers by Gustafson and Kotter (2017)and Cho (2017) examine the state-level variation of MWs in the U.S. using a sample of publicly traded firms, and find that MW hikes have a negative impact on investment.

Our study makes three main contributions to the assessment of MW effects. First, our research builds on the large geographical and inter-temporal variations of MW policies in China, where the MW varies across more than 2,800 counties. During our sample period (1998-2008), China implemented more than 17,000 local MW changes, more than half of which were greater than 10%.

Second, we use a census dataset that comprises the entire universe of Chinese manufacturing firms allowing us to focus on a sample of representative firms (not only large but also small and medium firms) that MW policymakers and scholars concern most. We pinpoint each firm's precise location by converting address information to geographical coordinates (longitude and latitude) and thus provide an improved empirical strategy, as discussed below.

Third, we examine the discontinuities of MW policies at county borders and investigate the effects of MWs on firms located around these borders that are subject to different MW policies. We construct all contiguous county-pairs in China and, within each pair, retain firms that are located within a short distance (i.e., 100, 75, and 50 km) of the shared border.[5] Firms located around county borders constitute good counterfactual pairs, as

[4]For example, those confounding factors include local credit expansion, labor supply, etc.
[5]A large number of observations remain after restricting the sample thanks to the rich dataset.

those in geographically proximate areas demonstrate a sufficiently high level of similarity in terms of credit and labor supply, proximity to public infrastructure (e.g., airports, railways, and sea or inland ports), market access, natural resource endowments, and unobservable factors such as local cultural characteristics. As pointed out by Arindrajit *et al.* (2010), a key advantage of the county-pair approach is that for each treated county, a neighboring county can be directly assigned as a control that shares a high degree of similarity with the treated, whereas in the traditional fixed effects approach any randomly chosen county is assumed to be as good a control as any other. We sharpen our empirical strategy by excluding any cross-province county-pairs, as areas from different provinces are likely to be subject to different regulatory regimes.[6]

The empirical results show a significant positive effect of MWs on corporate investment and support the *capital-labor substitution* hypothesis. In the sample of 119,229 distinct firms located within 100 km of shared borders of contiguous counties, a 10% increase in the MW corresponds to a 0.54 percentage points increase of investment, defined as capital expenditure relative to total assets, amounting to 5.2% of the sample average. The economic magnitude of this estimate is sizable considering the average growth rate of MW is 10.7% per year during the sample period. The regression results are qualitatively robust when including various firm controls, macroeconomic controls, and a rich set of fixed effects that eliminate time-varying differences across provinces and industries, permanent individual firm effects, and, most importantly, spatial heterogeneities common to geographically proximate areas (contiguous county-pair fixed effects). In additional analyses, we find MW is significantly positively related to the ratio of the capital stock relative to labor. The estimated coefficient implies that MW elasticity of the capital to labor ratio is 0.126. These combined findings suggest that firms shift away from labor toward capital, as a response to MW hikes.

We cement our capital-labor substitution hypothesis by exploring heterogeneous effects of MW shocks in four dimensions based on extant theories. We first strengthen our results by examining a direct measure of MW hike exposure, labor intensity. Our findings indicate that MW hikes matter more for firms in labor-intensive industries, as these firms normally hire a large proportion of MW-earning workers and are thus more exposed to MW shocks.

The second dimension of heterogeneity we examine is product market competition. The literature suggests that firms may pass labor costs on to consumers through price increases.[7]

[6] As a robustness check, our results are quantitatively and qualitatively similar if we exclude county pairs straddling two cities.

[7] See Aaronson (2011) and Aaronson and French (2007) for evidence that a firm's response to MW depends on the pass-through of the increased labor costs.

However, the pass-through of increased labor costs depends on the degree of competition, as this determines firms' ability to adjust their markup (Vives (2001); Lu and Yu (2015)). As a result, firms in a competitive industry are less subject to the price effect of a MW increase and are thus more incentivized to capitalize the labor share in production. We accordingly find that the effect of MW on investment is stronger for firms in industries with a higher degree of competition, as gauged by either the market concentration measure (the Herfindahl-Hirschman Index) or the Lerner Index that is constructed following Philippe *et al.* (2005).

The third dimension of heterogeneous effects is access to finance. A constrained access to capital drives up the capital rental relative to labor wage, thereby discouraging firms from investing in labor automation. The adverse effect of constrained capital access is particularly severe among private firms, as their investment depends highly on the availability of bank credit (Ayyagari *et al.* (2010)). As our sample mainly contains private firms, we follow Jayaratne and Strahan (1996) and use the penetration of bank branches in a city to proxy for the availability of credit.[8] Intuitively, higher density of bank branches means less friction in the credit market and more credit supply. We find the treatment effect of MW is stronger for firms located in cities with high bank density.

The fourth dimension of heterogeneity we examine is how the legal environment affects the relation between MW and investment. Contract enforcement is a critical determinant of corporate investment (North (1990)), as firms are reluctant to invest if the proceeds from their investment cannot be effectively protected (Johnson *et al.* (2002)). The negative consequence of this "grabbing hand" concern on investment is a worldwide problem (Shleifer and Vishny (2002)). Consistent with these findings, we find that the effect of MW hikes on investment is stronger in regions with a better legal environment.

To offset the negative effects of MW, firms need to improve their productivity by acquiring labor-saving technologies externally or developing such technologies internally. The source of productivity improvement is thus of interest. The regression results indicate MW is significantly positively correlated with the innovation output measured by patent count, implying firms adapt to the adverse labor shocks by investing in their in-house R&D team. Our findings reveal that the higher wage floor motivates firms to shift toward an innovation-oriented business strategy. Our findings complement the previous studies that the availability of low-cost labor can hinder the adoption of new technology (see Lewis (2011); Bena and Simintzi (2015)).

[8] A Chinese county is a division administered by a prefectural city, which is in turn administered by a province. County, prefectural city, and province represent the top three levels of China's administrative divisions.

Finally, we study the source of financing for the capital-labor substitution process. As discussed above, constrained credit access tends to moderate the effect of MW hikes. If bank credit is indeed the source of financing for the automation process, we should observe a corresponding change on the balance sheets of firms, specifically in the long-term debts that are used to finance capital investment (Vig (2013)). Our regression results show that MW is statistically positively related to long-term leverage, as measured by long-term debts divided by total assets. In addition, our analysis reveals that firms adjust their debt structure toward a higher share of long-term debts in total debts, and thus a longer maturity. Overall, our findings demonstrate that external financing plays an important role in shaping how MW affects firm investment behavior.

This study contributes to the literature on the consequences of MW policies for the real economy. Although the employment effect of MW is extensively discussed (e.g., Card and Krueger (1994, 1995, 2000); Sorkin (2015); Meer and West (2016); Jardim *et al.* (2017)), how firms alter their investment policy to adapt to MW hikes is less clear. Little evidence of capital-labor substitution is found using listed companies (Gustafson and Kotter (2017); Cho (2017)). Using the large county-level variation in MW and census data covering all Chinese manufacturing firms, we find a strong investment response to MW hikes and provide the first evidence for a capital-labor substitution channel, through which MW policies transmit to corporate investment policies. Our findings highlight MW policies can create economic value-added in the long run. This study adds to the literature on the dynamics of capital and labor in the era of automation. Prior studies suggest that the availability of less-skilled labor leads to a lower capital intensity and impedes automation and innovation (Lewis (2011); Hornbeck and Naidu (2014); Bena and Simintzi (2015)). New technology adoption (e.g., the use of computers or robots) can alter skill demands (Autor *et al.* (2003)) and reduce employment, particularly for routine manual occupations (Acemoglu and Restrepo (2017)). Complementing these works, we note that regulations that increase the price of labor input can accelerate the substitution of labor into capital goods and increase productivity by incorporating new technologies. This study also contributes to the literature of labor and finance. Although MW policy is a key element in labor regulation, it is underexplored in the finance literature. Our study adds to the discussion of how wage and employment policy are related to research topics in finance (e.g., Ellul *et al.* (2017a); Michelacci and Quadrini (2009)). By examining the impact of MW on firms in a newly identified channel, our analysis is related to recent studies that examine the impact of labor forces on investment (Besley (2004)), financing (e.g., Simintzi *et al.* (2015); Lin *et al.* (2016); Ellul *et al.* (2017b); Baghai *et al.* (2017)), and corporate innovation (Chang *et al.* (2015); Bradley *et al.* (2016)).

2 Empirical Design and Data

2.1 Minimum Wage Regulation in China

The MW policy in China provides us with a unique and rich institutional setting to study the impact of labor on corporate investment policy. As an important component of labor law legislation, the MW provision came into effect in 1994. Article 48 of the contemporaneous labor law authorizes provincial governments to set the local MW, which can vary across counties within the same province. Lower-level authorities, such as city-level and county-level governments, can negotiate local MWs with their respective provincial authorities and therefore have substantial influence over MW policy in their respective administrative areas (Casale and Zhu (2013)). Provincial authorities are responsible for reviewing these policies and monitoring policy enforcement. As for determinants of MW, prior studies conclude the timing of the MW change is largely determined by internal party politics, which is regarded as an exogenous factor (Huang *et al.* (2014)).

The MW data are directly sourced from the Ministry of Human Resources and Social Security (MOHRSS) and the Chinese Academy of Labor and Social Security. The dataset covers MWs of all counties in China between 1996 and 2012. To match firm financial data reported annually, we construct an annual MW measure by multiplying the December MW by 12 and use this annual MW measure to predict corporate investment in the next year. [9] Firm financial data, including corporate investment information, are up to 2008, so we use MW data up to 2007.

Nationwide MWs experience rapid growth during the sample period. The mean MW in China was CNY2,393.6 per year in 1998, which more than doubles to CNY5,827.8 in 2007. On average, the growth rate of MWs over the sample period is 10.7% per year with a large standard deviation of 9.3%. Li *et al.* (2012) document a similar pattern, finding that China's wage growth starts to pick up in the late 1990s. MWs in China feature large cross-sectional and intertemporal variations. In Figure 1, we present the geographical distribution of MWs across China in four diagrams, each representing a selected sample year. In each diagram, we sort counties into quintiles according to their respective MW values, with each quintile

[9] The MW is separately specified for monthly wages, part-time hourly wages, and full-time hourly wages. As hiring in the manufacturing sector usually involves vocational training, the employment contracts are relatively long and stable. We therefore choose to use the full-time monthly MWs in our analyses, due to its relevance to the manufacturing sector.

marked by a different color. A significant geographical variation in MWs can be observed in each of the diagrams in Figure 1. In addition, most counties shift their quintiles over years, as noted by the changing colors assigned to these counties. This suggests the relative ranking of a county in terms of MWs does not stabilize but changes substantially over time.

2.2 Firm-Level Data

We draw the firm-level data for the 1998-2008 period from the Chinese Industrial Enterprise Dataset (CIED), sourced from the National Bureau of Statistics (NBS). NBS conducts an annual survey of all of the industrial firms with annual sales above CNY 5 million (USD $710,000 at the exchange rate at the end of 2008) and publishes the survey data in the CIED. For each surveyed firm, the dataset reports detailed financial information retrieved from annual financial statements. The survey data have missing or abnormal values. We filter the data following the literature and report details of the filtering process in Appendix 2. All financial variables of CIED are winsorized at a 1% level to mitigate effects of outliers. We further drop firms in the utility sectors (four-digit industry codes 4400-4499 and 4600-4699), as these firms can be under strict regulation. According to Brandt *et al.* (2012), the industrial firms surveyed in 2004 represent more than 90% of the total manufacturing output and more than 70% of the employment in manufacturing industries, demonstrating the comprehensive coverage of our dataset.

The CIED reports ownership information, which allows us to categorize firms into three ownership types: i) private, ii) state, and iii) foreign ownership. We take a conservative approach and keep only privately owned firms that feature relatively homogeneous characteristics in our sample, thus avoiding any selection bias created by ownership type. In the robustness checks, we find qualitatively similar results in the samples of state-owned enterprises (SOEs) and foreign firms.

2.3 Empirical Strategy

Identifying the effects of MW on corporate investment is challenging, as the determinants of MW may not be orthogonal to economic fundamentals or firm characteristics. A key objective of the empirical strategy is to ensure that the estimated treatment effect of MW on investment is not tainted by local business cycles or other omitted variables. To overcome the endogeneity problem, we take advantage of the discontinuities of MWs at county borders and directly compare the investment behavior of firms located within a pair of contiguous counties that may adopt different MWs. Contiguous counties act as good controls because their geographical proximity tends to minimize effects of omitted factors, while also exhibiting variations in MW. The identification of all of the contiguous county pairs relies on a digital map of China, sourced from the China Data Center at the University of Michigan. We drop any cross-province county pairs that straddle two provinces to prevent endogeneity being introduced from other sources, such as different regulatory patterns and business cycles. We then merge the contiguous county-pair dataset with the firm-year panel. As a county can border multiple neighboring counties and thus appear in multiple county pairs, a firm-year observation located in such a county can repeatedly appear in the dataset; each instance is identified by a distinct county pair in our regression sample.

The contiguous county-pair identification strategy assumes firms and labor do not mobilize in response to MW hikes. First, we argue that a firm's location decision in China is not likely to be affected by MW policy. The relocation of a manufacturing company often involves purchasing land parcels, which is strictly controlled by the government, and building new plants would require government approval that imposes very high costs on the firms. Second, it is theoretically possible that firm wage expenditure in a low-MW area would increase due to the reduced labor supply, as workers may be attracted to a neighboring county paying a higher MW, and thus weaken the treatment effects of MW hikes. In fact, labor mobility driven by MW would bias our estimate downward. All else being equal, our finding should be stronger if labor mobility is less of a concern.

Our focus is on firms located near county borders, so we pinpoint the precise firm location by converting the firm address information provided in the CIED to two-dimensional geographical coordinates (longitude and latitude). To ensure the accuracy of the address conversion, we use three major geo-coding service providers (Google, Gaode, and Baidu) to cross-check the quality of the location identification. [10] We remove from a county pair any firms located outside a specified distance to the shared border of the county pair (within 100, 75, or 50 km). We further require each county in a county pair to contain at least five firms in each year. The largest sample (100 km) consists of 1,864,513 observations featuring 407,342 firm-years, 119,229 distinct private firms, and 4,205 contiguous county pairs.

Following studies that investigate the effect of public policies on firm-level investment (e.g., Ellul *et al.* (2010)), we model corporate investment as a function of MW and estimate

[10] If a firm's coordinates generated by the three providers do not match, we calculate the distance between any two of the three sets of coordinates and use as firm location the midpoint of the two sets of coordinates that feature the shortest distance.

the following regression specification

$$Investment_{i,c,p,t+1} = \beta_0 + \beta_1 \ln(MW_{c,t}) + \beta_2 X + \theta_p + \delta_i + \rho_{s,t} + \sigma_{k,t} + \varepsilon_{i,t+1} \qquad (1)$$

where the i, c, p, s and k subscripts stand for firm, county, contiguous county pair, province, and industry, respectively. The dependent variable, $Investment$, denotes the corporate investment measured by the change of net fixed assets plus the current depreciation relative to the total assets. $\ln(MW)$ denotes the log value of December MW multiplied by 12. X is a vector of the firm-level control variables, which include firm size ($\ln(Assets)$), a measure for the amount of tangible assets in firms $Tangibility$, profitability defined as profits divided by total assets ROA, and growth opportunities proxied by sales growth rate $\Delta Sales$. We add to the control variables several macroeconomic variables to account for any effects from macroeconomic conditions. These macroeconomic variables are measured at the level of the city that administers the corresponding county and include the log GDP per capita $ln(GDP\ per\ Capita)$, the growth rate of GDP ΔGDP, and the growth rate of foreign direct investment ΔFDI. The data for macroeconomic variables are taken from the CEIC Premium China Database. All explanatory and control variables are lagged by one year to reduce the risk of reverse causality.

A number of fixed effects are also used. County-pair fixed effects (θ_p) capture spatial heterogeneities operating around the shared border of two contiguous counties. Prior studies document MW changes affect the industry dynamics of firm entry and exit (e.g., Aaronson *et al.* (2018)). We thus include firm and use the inter-temporal variation in MW for identification. We also control province-by-year fixed effects $\rho_{s,t}$ and industry-by-year fixed effects $\sigma_{k,t}$ to remove any time-variant shocks at the province and industry levels, respectively. The industry classification is based on three-digit industry codes. We cluster robust standard errors at the county-pair level.

2.4 Summary Statistics

Table 1 presents descriptive statistics for the regression variables. Panel A reports dependent variables measured in a one-year lead, compared with the explanatory and control variables on the right-hand side of the regression. We measure $Investment$ by the change of net fixed assets from t to $t+1$ plus the current depreciation in year $t$scaled by the total assets at the end of year t. To demonstrate that the results are not driven by our particular variable definition, we develop two alternative measures for investment, $Investment1$ and

$Investment2$, the former excluding the current depreciation and the latter based on the change of original value of fixed assets. The mean of $Investment$ in the sample is 0.104 with a standard deviation of 0.256, indicating the sample firms make substantial capital expenditures over the sample period. Capital intensity ($\ln(K/L)$) is the log value of net fixed assets divided by the number of employees. Firm patent output ($Patent$) is the number of granted patents filed in a year. On average, the sample firms produce 0.171 patents annually. The log value of one plus the patent count is used in the regression. [11] Panel A also reports the summary statistics for financial leverage. A notable feature of the sample is the low share of long-term debt in the capital structure of firms. The mean of *Debt Structure*, as measured by long-term debts maturing over one year relative to total debts outstanding, is 8%, although on average the total debts outstanding accounts for 59.1% of the total assets, as shown by the mean value of *Total Leverage*.

[Table 1 about here]

Panel B reports the county-level variables based on 21,327 county-year observationswhere the necessary information is available. The mean MW across all Chinese counties is CNY3,953 with a variance of 1,383. Other firm-level control variables are presented in Panel C. We consider two proxies for firm-level labor costs: $ln(AW)$ is the log value of average wage per worker and $ln(TW)$ is the log value of a firm's total wage expenses. The detailed variable definitions are given in Appendix 1.

3 Main Evidence

This section presents the empirical results of our analyses on the impact of MW policy on corporate investment. We begin with a validity test to show the relevancy of MW to firms' labor costs. We then present the baseline findings, followed by the heterogeneous effects along four dimensions. Potential mechanisms behind our baseline findings are also discussed.

3.1 The Effectiveness of MW Policy

Our research builds on the premise that MW adjustments represent a meaningful elevation in labor costs across firms. Survey evidence shows that MW materially affects firms' labor costs. For example, in a survey conducted by the Chartered Institute of Personnel

[11] Following the practice in the literature, we add one to the number of patents to avoid losing observations with zero patents.

and Development and the Resolution Foundation, over half of 1,037 surveyed employers (54%) said MW hikes would have an effect on their wage bill, with 18% of those employers claiming they would be affected to "a large extent."

Our comprehensive sample consists of all Chinese manufacturing firms, most of which are labor-intensive and should be affected by MW hikes to a large extent. To formally validate this assumption in our sample, we regress firm wage expenditures on the local MW and a set of the firm-level control variables. Firm wage expenditure is proxied by two empirical measures: average wage expenditure $ln(AW)$, defined as the (log) firm total wage expenditure divided by the number of employees; and total wage expenditure $ln(TW)$, defined as the log value of firm total wage expenditure. The regression results given in Table 2 suggest that MW is a significantly positive explanatory variable on firm wage expenditure across different models. As indicated in Table 2, Column 1, a 10% increase in MW leads to an increase in firms' average wage per employee of more than 5%. The coefficient remains both statistically and economically significant when firm fixed effects are included.[12] Our results suggest MW policy is indeed binding in this research context. The adverse effects of MW on the wage costs of the sample firms are material and cannot be ignored when they make investment decisions.

[Table 2 about here]

We next explore what actually determines the MW policy in a county, and more importantly whether the decision for MW adjustment is dependent on the investment policy of firms in the county. We model a binary variable of MW change as a function of the county-level investment measure, the county-level capital intensity measure, and macroeconomic factors including GDP per capita and foreign direct investment (FDI). Both county-level investment and capital intensity measures are constructed by averaging firm-level investment and capital intensity measures of all firms in a county. The regression results are tabulated in Appendix 3. We find none of the regressors exhibits statistically significant explanatory power. Notably, the insignificant estimates of county-level investment and capital intensity measures suggest the reverse-causality concern may only bias our baseline specification to a very limited extent. Although these results are informative, it would be overstating it to say that MW policy setting is purely random and free of influences of other omitted variables. Therefore, we take the contiguous county-pair approach discussed above to gain causal inference.

[12]The results remain largely unchanged if none of the firm-level control variables are included in the regression.

3.2 Baseline Results

In Table 3, we present baseline results for the regression specification given in Eq. (1) for three samples, where county pairs include firms located within 100, 75, and 50 km of the shared border, respectively. We find that MW is a statistically positive explanatory variable for corporate investment, and the results are robust across the different distance cutoffs. The economic magnitude of the MW is also sizable. For instance, in the sample using 100 km as the cutoff, the point estimate of $ln(MW)$ at 0.054 in Column 1 of Table 3 indicates a 10% increase in MW implies an increase of Investment by 0.54 percentage points, which amount to 5.2% of the mean Investment in the sample. Considering the rapid growth of MW at 10.7% per year, the economic impact of MW can be enormous during the sample period. As we further restrict sample firms to those located closer to borders, firms located on opposite sides of the borders should be subject to a more similar economic environment, and the regression estimate should be more accurate. In Columns 2 and 3, where we restrict the sample to firms located within 75 and 50 km of the borders, we find that the coefficient estimate of $ln(MW)$ remains quantitatively and qualitatively similar as the sample shrinks. Our findings from the baseline regressions support the capital-labor substitution hypothesis, which suggests that firms increase their capital investment to offset rising labor costs.

[Table 3 about here]

3.3 Robustness Checks

We conduct several robustness checks to strengthen our empirical findings. First, to demonstrate that the choice of corporate investment measure is not up to our discretion, Panels A and B of Table 4 repeat the regression specifications in Table 3 with two alternative measures for corporate investment ($Investment1$ and $Investment2$). $Investment1$ excludes the current depreciation in the construction of investment measure and $Investment2$ is based on the change of original value of fixed assets. The estimated coefficients of $ln(MW)$ are statistically significant and positive in the regressions of both alternative measures for investment. Unsurprisingly, the effects of $ln(MW)$ are weaker in Panel A because the exclusion of depreciation mechanically reduces the magnitude of the investment measure.

[Table 4 about here]

Second, in China, a city is a higher administrative authority than a county and some county pairs straddle more than one city. The captured MW effects in the baseline regressions may be distorted by omitted variables operating at the city level. We thus drop from the sample county pairs straddling two cities and keep only those where both counties are under the jurisdiction of the same city. Panel C reports regression results in the refined sample, and the effects of MW are qualitatively and quantitatively similar to those reported in the baseline results, suggesting a limited effect of omitted city-level heterogeneities on our baseline estimates.

Third, our analyses draw on a sample of privately owned firms, as the other two ownership types (i.e., state and foreign ownership) are associated with other confounding factors. State-owned enterprises (SOEs), for example, are subject to more restrictions over firing workers and receive more favorable credit allocations (Bai, Lu, and Tao, 2006; Li, Meng, Wang, and Zhou, 2008). These traits predict the contradictory impact of MW on the capital-labor substitution process. Although our hypothesis does not provide a clear prediction of how these other ownership types distort firms' response to MW, [13] we repeat the regression specification in Eq. (1) in samples of SOEs and foreign firms, and report the regression results in Panels D and E, respectively. We find the effects of MWs are qualitatively similar in both samples, suggesting our baseline findings are not dependent on the discretionary choice of a particular ownership type.

3.4 Capital-Labor Substitution: More Evidence

Our analysis so far indicates the positive effects of MW on corporate investment but provides little evidence for the dynamics of factor substitution in production. Consistent with prior studies (e.g., Acemoglu and Finkelstein, 2008), we construct capital intensity measure as the capital-labor ratio. We thus directly estimate the effect of MW on the substitution between capital and labor using the following regression specification:

$$In(K/L)_{i,t+1} = \beta_0 + \beta_1 \ln(MW_{c,t}) + \beta_2 X + \theta_p + \delta_i + \rho_{s,t} + \sigma_{k,t} + \varepsilon_{i,t+1} \tag{2}$$

where $ln(K/L)$ denotes the log of the capital stock relative to the number of employees. Other model specifications follow the convention in Eq. (1).

[Table 5 about here]

[13] For example, in response to MW hikes, foreign firms can either engage in capital-labor substitution due to the technology advantage of their overseas parent firms, or invest less because the particular group of foreign firms setting up subsidiaries in countries with low labor costs lack the motivation for innovation (Bena and Simintzi, 2015).

We report the regression results in Table 5. The coefficient estimate of $ln(MW)$ is statistically significant at the 1% level across all three samples of the 50-, 75-, and 100-km cutoffs. The point estimate at 0.137 implies that a 10% increase in MWs leads to 1.37% more capital stock relative to the labor. As the growth of the nationwide average MW is rapid, the accumulated effects of MWs on the dynamics of factor substitution in the Chinese manufacturing sector are non-trivial. The coefficient remains robust (0.126) in the sample of firms located within 50 km of the county borders. These findings further confirm our capital-labor substitution hypothesis and provide a new perspective on how firms adapt to an adverse labor shock by adjusting their employment policy in conjunction with their investment policy.

3.5 Heterogeneities

In this subsection, we examine the heterogeneous effects of MW on firms' investment choices along four theoretically predicted dimensions. Two dimensions examine industry-level heterogeneities (labor intensiveness and market competition) and two examine geographical heterogeneities (bank credit availability and legal environment).

3.5.1 Heterogeneity According to Labor Intensity

MW hikes directly push up a region's ground wage, so firms' exposure to MW adjustments varies according to their wage structure. MW policy should matter more to firms operating in labor-intensive industries that typically pay employees wages close to the local MW. If the positive association between MW and corporate investment is driven by the capital-labor substitution hypothesis, we expect that labor-intensive firms should spend more capital expenditure than their non-labor-intensive counterparts.

The measure for labor intensity follows Bell and Machin ((forthcoming). We first average the ratio of total wage expenditure to total assets across all firms in a three-digit industry in a given year, and subsequently obtain our labor intensity measure by averaging the industry-by-year measure generated in the first step across the sample period. Formally, the labor intensity measure is defined as

$$Labor\ Intensity_k = \frac{1}{T}\frac{1}{N_{k,t}}\Sigma_T \Sigma_{i\in k}\frac{Wage_{i,t}}{Size_{i,t}}$$

where $Wage$ denotes a firm's total wage expenditure, Size is the firm's total assets, $N_{k,t}$ is the firm count in industry k in year t, and T is the number of years in the sample period. We also generate a second labor intensity measure that is the same as the first, except it proxies $Size$ by firm sales. We sort all three-digit industries in our sample by labor intensity and label an industry as "high intensity" if its intensity measure is above the sample median, and as "low intensity" otherwise. We repeat the regression specification in Eq. (1) for both the high and low labor intensity subsamples and report the regression estimates in Table 6. In Columns 1 and 2, where we use the first labor intensity measure, the estimate of $ln(MW)$ at 0.104 in the subsample of "high intensity" is substantially larger than the estimate in the subsample of "low intensity". Following Cleary (1999), we test the difference in the coefficients estimated for the two subsamples and reject the null hypothesis that the coefficient estimates for $ln(MW)$ are the same at the 1% level. The findings in the subsample analysis suggest that the MW effects on investment are more pronounced for labor-intensive firms, and further support the capital-labor substitution hypothesis underlying our baseline findings. [14]

[Table 6 about here]

3.5.2 Heterogeneity According to Product Market Competition

MW studies have shown how and to what extent MW hikes affect prices of goods and services.[15] As laid out in standard economic theories, firms can pass the MW-induced labor costs on to consumers by raising product prices. Empirical evidence supporting these theories find that in the U.S., restaurant prices are positively correlated with MW (Aaronson (2001); Aaronson *et al.* (2008)). Therefore, the dynamics of capital and labor induced by a rising wage floor is contingent on the possibility of this pass-through process.

From a theoretical perspective, markups tend to diminish as the number of competing firms grows, if their products are homogeneous (Vives (2001)). Firms in a competitive industry are less capable of adjusting their product prices upward when hit by a regional labor costs shock, such as MW hike, that only affects firms operating in a particular geographical area. [16] The impaired pass-through channel thus forces firms operating in competitive industries to respond to MW hikes more swiftly.

We construct two measures to gauge industry competition. The first is based on the Herfindahl-Hirschman Index (HHI) that aggregates the squares of the market shares of the

[14] Our results remain qualitative and quantitatively similar if we partition the sample using the median of the industry-by-year measure of labor intensity.

[15] See Lemos (2008) for a survey.

[16] MW policy is at the region level so that it can only affect a proportion of firms in a particular industry.

firms within a three-digit industry. Formally, it can be expressed as

$$HHI_k = \frac{1}{T}\Sigma_T \Sigma_{i\in k} S_{i,t}^2$$

where $s_{i,t}$ is the market share of firm i in year t defined as the firm's sales divided by the aggregate sales for all firms of industry k in the same year. A small HHI_k indicates a competitive industry with no dominant players.

The second measure for product market competition is based on the Lerner Index or price-cost margin. The crucial advantage of the Lerner Index over the HHI is that it does not rely on a clear delineation of geographical markets (Philippe *et al.* (2005)), which is particularly difficult in our setting as many sample firms export. [17] The Lerner Index of firm i in year t is defined as

$$LI_{i,t} = \frac{OperatingProfit_{i,t} - FinancialCost_{i,t}}{Sales_{i,t}}$$

and the competition measure in a three-digit industry is characterized as

$$LI_k = \frac{1}{T}\frac{1}{N_{k,t}}\Sigma_T \Sigma_{i\in k} LI_{i,t}$$

where $N_{k,t}$ is the number of firms in a three-digit industry k in year t . is the number of sample years.

[Table 7 about here]

We partition all three-digit industries in our sample by the median of each competition measure, and mark the industries below median HHI_k (below median LI_k) as "high competition" and the industries above median HHI_k (above median LI_k) as "low competition". In Table 7, Columns 1-2 report the regression results in subsamples divided by the median HHI_k, and Columns 3-4 by the median LI_k. Under both partition schemes, we find that the coefficient of $ln(MW)$ is highly statistically significant in the "high competition" subsample, whereas the coefficients in the "low competition" subsample is statistically insignificant. The estimate at 0.063 in Column 1 is 70.2% higher than that in Column 2 of 0.037. The statistical test rejects the null hypothesis that the coefficient estimates for $ln(MW)$ are the same at the 1% level. The subsample analysis by industry competition suggests our baseline findings are mainly driven by firms operating in competitive industries that cannot pass the

[17] Gan *et al.* (2016) find that 29% of manufacturing firms are in the CIED export.

increasing labor costs on to consumers. The findings highlight that product market competition is an important consideration, which can reshape a firm's response to MW policy. [18]

3.5.3 Heterogeneity According to Access to Credit

Access to external finance such as bank loans is a critical determinant of firm investment behavior, particularly for firms in a transition economy (McMillan and Woodruff (2002); Cull and Xu (2005)). Good access to the capital market is vital for the labor automation process, as firms may need to finance their capital investment. We thus hypothesize that firm investment is more sensitive to MW hikes if the credit supply in the area is less constrained. Due to the private nature of our sample firms, bank credit is the major source of external financing. Consistent with the literature (e.g., Jayaratne and Strahan (1996)), we use the penetration of bank branches in an area as a proxy for the availability of credit financing. Intuitively, a higher bank branch count will signal the availability of credit resources in an area. We collect data on bank branch information from the China Banking Regulatory Commission (CBRC) and count bank branches for each city.[19] Figure 2 shows that the distribution of bank branches features a significant geographical variation in China, implying a substantial difference in the extent of credit availability across Chinese cities. In addition, the penetration of bank branches intensifies over years. On average, the number of commercial bank branches per city is 218 in 1998 and this figure increases to 380 by 2008. Despite the rapid penetration of bank branches, the relative ranking of Chinese cities in terms of bank branch count remains relatively persistent over time, as shown in Figure 2. This pattern is consistent with the notion that credit allocation and the related bank clustering are largely determined by non-economic factors, such as the scale of local state-owned enterprises. We therefore argue that commercial bank penetration is relatively exogenously determined and orthogonal to MW policy.

[Figure 2 about here]

To gauge bank penetration in a city, we define bank branch density as the bank branch count divided by the city's population. We sort all of the cities in our sample based on

[18] Our results remain robust if the sample is split according to the median of the industry-by-year measure of industry competition.

[19] We consider all types of commercial banks, including major state-owned commercial banks, city commercial banks, postal savings banks, joint-equity commercial banks, privately owned banks, rural commercial banks, and foreign banks.

bank branch density, and then group cities above the sample median of bank branch density measure into the "high bank penetration" subsample and others into the "low bank penetration" subsample. Any county pairs straddling two cities are excluded because the two counties within such county-pairs may be subject to different levels of credit availability. The regression results in Table 8 show that MW hikes only have material effects on corporate investment decisions of firms located in areas with abundant credit resources. The findings point to the important role of credit availability in facilitating/restraining firm investment behavior driven by MW changes.

[Table 8 about here]

3.5.4 Heterogeneity According to Legal Environment

Contract enforcement (or an effective judicial system) is an important determinant of economic growth (North (1990)). Firms' investment decisions are conditional on whether they can legitimately harvest the fruits of their past investment (Johnson *et al.* (2002)). Specifically, the property-rights protection over the physical capital, profits, and patents thus incentivizes firms to invest and innovate. In contrast, in a malfunctioning legal environment, governments, or more accurately politicians, may extract rents from the investment proceeds. This "grabbing hand" concern can depress firm investment in an economy (Shleifer and Vishny (2002)), and is supported by several empirical studies. At the country level, property rights protection is positively associated with aggregate investment and economic growth (e.g., Acemoglu and Finkelstein (2008)). At the micro-level, Cull and Xu (2005) find that one aspect of property rights, the ease and reliability of contract enforcement, is a significant predictor of a firm's investment. In this study, we extend this idea to our analysis by examining whether a better legal infrastructure facilitates capital investment resulting from MW hikes. We predict that firms are less willing to invest in labor automation if their incentive for investment has already been discouraged by poor property rights protection.

As suggested by Cull and Xu (2005), the effectiveness of Chinese legal institutions varies across regions. Specifically, China had been undergoing a reform moving China toward a market-oriented economy during the sample period, and the legal framework development is one important component of the reform. However, this market reform takes place at a different pace in each area, as noted by previous studies (Firth *et al.* (2009)). To explore this institutional heterogeneity, we use the index developed by Fan and Wang (2006), who rate the legal framework development of each Chinese province, and evenly sort all provinces in our sample into two subsamples. In theory, firms based in areas with more developed legal frameworks will make more capital investment when facing MW hikes. As this index for the legal environment is relatively persistent, we use the index of 1997, which is one year ahead of the starting year of our sample period. This practice mitigates the potential endogeneity concern that this time-varying index may correlate with MW during our sample period.

We again estimate the baseline regression specification in Eq. (1) in the two subsamples based on the legal environment. The regression results are reported in Table 9. Consistent with our prediction, the coefficient of $ln(MW)$ is highly statistically and economically significant in the subsample of the high legal environment, but loses its significance in the low legal environment subsample. Our findings provide evidence that the legal system plays an important role in the interaction between labor market policies and corporate investment.

[Table 9 about here]

4 Other Firm-Level Responses

In this section, we provide additional supporting evidence that MW hikes incentivize firms to shift from labor-intensive to capital-intensive operations, by examining their patent outputs and financial leverage.

4.1 Corporate Innovation

The main hypothesis of this study is that MW hikes restrict firms' access to cheap labor and create incentives for them to adopt capital goods embodying labor-saving technologies. However, any marginal increment in capital investment does not necessarily displace labor if there is no readily available technology to be acquired. Firms have to be self-reliant to develop necessary technologies for labor automation. This MW-driven technology upgrade is very likely to occur in China, where cheap labor is believed to be the main advantage in global competition (Li *et al.* (2012)).

R&D expenditure is useful in capturing the amount of money invested in innovation activities. However, R&D data can be problematic. Missing values are commonly documented in the literature (e.g., Koh and Reeb (2015)), so care should be taken when drawing inferences based on R&D variables. The R&D variable in the CIED contains a large proportion of missing values, so the problem is potentially severe. [20] Firms may also wrongly categorize other expenses to R&D expenditure to benefit from tax credit. [21] The incentive for

[20] More than 90% of firm-year observations have missing values for the R&D variable in CIED.
[21] For example, Chen et al. (2017) find firms are likely to relabel administrative expenses as R&D.

tax credit cheating thus makes the R&D variable less reliable. Instead, following previous studies of corporate innovation (see He and Tian (2017), for a review), we use patent counts to capture a firm's innovation activities. Patent count can be a more effective measure of a firm's innovation capacity and productivity than R&D expenditure, as it directly captures the innovation output. We match our sample firms with patent data published by the State Intellectual Property Office (SIPO) and estimate the following regressions specification:

$$In(1 + Patent)_{i,t+1} = \beta_0 + \beta_1 \ln(MW_{c,t}) + \beta_2 X + \theta_p + \delta_i + \rho_{s,t} + \sigma_{k,t} + \varepsilon_{i,t+1} \tag{3}$$

where the dependent variable $In(1 + Patent)_{i,t+1}$ denotes the (log) one plus the number of patents filed by firm i in year $t + 1$. Following Hall *et al.* (2001) and Acharya *et al.* (2013), we use the patent filing date to proxy for the true invention date, as this is the closest date to the true date. Patent data in SIPO do not include any citation information, so we cannot differentiate the value of a patent by its future citation count. Table 10 reports the regression estimates for the specification given in Eq. (3). The key variable of interest $ln(MW)$ is significantly positively related to firm innovation output measured by patent count. The effect is also economically significant. The coefficient implies that an increase of one standard deviation in MW leads to a 6.2% increase in the number of patents relative to the sample mean of the patent count. Our findings suggest that a negative shock in the labor market can actually encourage corporate innovation. The evidence complements findings that the availability of cheap labor (resulting from globalization, migration, etc.) hinders innovation and technology adoption (Lewis (2011); Hornbeck and Naidu (2014); Bena and Simintzi (2015)).

[Table 10 about here]

4.2 Financial Leverage

As discussed in Subsection 3.5.3, the labor displacement process resulting from MW hikes is critically contingent on a firm's access to external finance. Thus, we conjecture firms tend to adjust their capital structure accordingly to cope with the financing of capital investment. Due to the nature of private firms, most of the sample firms rely on bank credit as the main source of financing. We therefore examine how financial leverage changes in response to MW hikes. In particular, our interest is in long-term financial leverage, as the financing period for capital investment usually spans more than one year. We use two leverage metrics related to long-term debts: *Long Leverage*, defined as the long-term debts that mature over one year relative to the total assets, and *Debt Structure*, defined as the long-term debts relative to the total debts. The former assesses the share of long-term debts financing relative to aggregate debts and equity financing (i.e., total assets), and the latter assesses the composition of a firm's debt. We also present a third leverage metric, $Total\ Leverage$, which is defined as total liability including both long- and short-term debts relative to total assets. As the short-term debts primarily constitute the liabilities of the sample firms, our hypothesis provides limited insights into the effects of MW hikes on short-term debts that are, in most cases, used to finance working capital (Vig (2013)). We model the financial leverage as a function of MW using the following specification:

$$Leverage_{i,t+1} = \beta_0 + \beta_1 \ln(MW_{c,t}) + \beta_2 X + \theta_p + \delta_i + \rho_{s,t} + \sigma_{w,t} + \varepsilon_{i,t+1} \tag{4}$$

where *Leverage* denotes one of three leverage measures.

The regression results are presented in Table 11. In Panel A, MWs represent a significantly positive explanatory variable for *Long Leverage* across three samples, implying the MW-induced capital investment is primarily funded by the long-term debts. In the sample using 50 km as the cutoff, a one standard deviation increase in MW leads to a 5.6% increase in *Long Leverage* relative to the sample mean. Similarly, the share of long-term debts relative to total debts, denoted by *debt structure*, is significantly correlated with MW, as shown in Panel B. The statistically positive coefficient estimate of $ln(MW)$ suggests that firms' debt structure shifts toward a longer maturity as a result of MW hikes. In contrast, the total leverage, denoted by $Total\ Leverage$, shows little response to MW hikes. This set of results complements our main evidence, and suggests that firms' adaption to MW hikes also involves a coordination of their financial policy.

[Table 11 about here]

5 Concluding Remarks

MW provision has been a controversial public policy. The debate surrounding the effects of MW on employment has continued since the first legislation in the U.S. in 1938, and appears to remain inconclusive despite lasting for almost a century.[22] However, except for the employment policy, the MW impact on the other behavior of firms has been overlooked

[22] Two academic studies investigating the recent MW hikes in Seattle reached opposite conclusions. See `https://www.economist.com/news/finance-and-economics/21724802-two-studies-their-impact-seattle-reach-opposite -conclusions-economists-argue`

in the literature. In this study, we examine the effects of MW on corporate investment. Unlike previous studies that assume firms passively pay the bill of MW hikes, this study reveals that firms actually adapt to an adverse labor shock in a more active manner such that they increase labor-saving investment to automate routine tasks that were previously carried out by MW-earning workers.

The analysis uses a census dataset of Chinese private manufacturing firms from 1998 to 2008, when Chinese counties experienced over 17,000 MW adjustments. This large variation in China's MW policy provides a good opportunity to address the endogeneity problems surrounding MW-related research. Our identification strategy relies on the discontinuities of MW policies at county borders. Firms located around the shared border of two contiguous counties can be subject to different MWs, but affected by similar economic and other omitted factors, due to their geographical proximity. A key advantage of our empirical strategy is that it enables us to tease out the treatment effects of MW, while controlling for omitted spatial heterogeneities that may bias our regression estimates.

The baseline regression results support our capital-labor substitution hypothesis that indicates a positive effect of MW on corporate investment. We also find that MW is a statistically positive predictor of the capital-labor ratio and patent outputs. To solidify our empirical findings, we explore four mechanisms through which MW affects corporate investment. We find that the effects are stronger for firms operating in labor-intensive industries, doing business in competitive product markets, with better access to finance, and located in areas with better property rights protection. The combined evidence demonstrates that firms adapt to the adverse labor shock by shifting away from their old labor-intensive business model and embracing a new capital-intensive model.

This study extends the MW literature by investigating the impact of MW on firm behavior other than employment. Our findings suggest that firms take a more active and holistic approach toward MW shocks by coordinating their employment policy with their corporate investment policy. The study provides a comprehensive perspective of the impact of MW policy, and contributes to the long-lasting debate among labor economists.

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Appendix 1. Variable Definitions

Variable	Definition
Firm-level Variables	
$Investment_{i,t}$	Change of net fixed assets from year $t-1$ to t plus current depreciation in year t scaled by total assets in year $t-1$; Source: CIED
$Investment1_{i,t}$	Change of net fixed assets from year $t-1$ to t without adding current depreciation divided by total assets in year $t-1$; Source: CIED
$Investment2_{i,t}$	Change of the original value of fixed assets from year $t-1$ to t scaled by total assets in year $t-1$; Source: CIED
$ln(K/L)_{i,t}$	Log value of net fixed assets divided by the number of employees. Source: CIED.
$Patent_{i,t}$	Number of new patents applied for by the firm in year t. Source: State Intellectual Property Office.
Long Leverage$_{i,t}$	Long-term debt divided by assets. Long-term debt is defined as debt that matures beyond one year, and short-term debt is debt that matures in one year. Source: CIED.
Debt Structure$_{i,t}$	Long-term debt divided by total debt outstanding. Source: CIED.
Total Leverage$_{i,t}$	Total debt scaled by total assets. Source: CIED.
ln(AW)$_{i,t}$	Log value of firm's average wage calculated as total wage expenditure divided by the number of employees. Source: CIED.
ln(TW)$_{i,t}$	Log value of firm's total wage expenditure. Source: CIED.
ln(Assets)$_{i,t}$	Log value of total assets. Source: CIED.
Tangibility$_{i,t}$	Ratio of net fixed assets over total assets. Source: CIED.
ROA$_{i,t}$	Return to assets defined as profits scaled by total assets. Source: CIED.
$\Delta Sales_{i,t}$	Sales growth rate from $t-1$ to t. Source: CIED.
County-level Variables	
$ln(MW)_{c,t}$	Log value of annualized minimum wage, defined as the monthly minimum wage of county c in December of year t multiplied by 12; Source: CIED.

$County\ Investment_{c,t}$	County-level investment measure defined as the size-weighted average of Investment across firms located in county c; Source: CIED
$County\ In(K/L)_{c,t}$	County-level capital-labor ratio defined as the size-weighted average of $ln(K/L)$ across firms located in county c; Source: CIED
$\Delta\ County\ Investment_{c,t}$	Growth rate of County Investment from year $t-1$ to t; Source: CIED
$\Delta\ County\ In(K/L)_{c,t}$	Growth rate of County $ln(K/L)$ from year $t-1$ to t; Source: CIED
$\Delta\ GDP_{c,t}$	Growth rate of GDP of the city that administers county c. Source: CIED.
ln(GDP per Capita)$_{c,t}$	Log value of GDP per Capita of the city that administers county c. Source: CIED.
$\Delta\ FDI_{c,t}$	Growth rate of foreign direct investment of the city that administers county c . Source: CIED.
$D_{t+1}^{\Delta MW}$	A binary variable with one representing a change in year $t+1$, and zero otherwise. Source: CIED.

Variables for Subsample Analysis

Labor Intensity: Wage/Assets	Labor intensity measure of a three-digit industry based on wage expenditure divided by total assets. We first average the ratio of total wage expenditure to total assets across all firms in a three-digit industry in a year, and subsequently obtain the labor intensity measure by averaging the industry-by-year measure generated in the first step across sample period. Source: CIED
Labor Intensity: Wage/Sales	Labor intensity measure of a three-digit industry based on wage expenditure divided by sales. We first average the ratio of total wage expenditure to sales across all firms in a three-digit industry in a year, and subsequently obtain the labor intensity measure by averaging the industry-by-year measure in the first step across sample period. Source: CIED
Competition: Lerner Index	Competition measure based on the Lerner Index of a three-digit industry. Following Aghion et al. (2005), we first average firm level price-cost margin, defined as $LI_{i,t} = (OperatingProfit_{i,t} - FinancialCost_{i,t})/Sales_{i,t}$, across all firms in a three-digit industry in a year, and subsequently obtain the competition measure by averaging the time-varying result in the first step across sample period. Source: CIED

Competition: HHI	Competition measure based on the Herfindahl-Hirschman Index of a three-digit industry. We first aggregate the square of the market shares of all firms within a three-digit industry in a year, and subsequently obtain this competition measure by averaging the time-varying result in the first step across sample period. The market share is defined as fraction of sales relative to the total sales in an industry. Source: CIED
Access to Credit	City-level measure of access to credit defined as the number of commercial bank branches in a city scaled by the city's total population in a year. Source: CIED.
Legal Environment	Province-level legal infrastructure development index in 1997, from Fan and Wang (2006).

Appendix 2. Sample Construction

The raw data from the China Industrial Enterprise Database (CIED) comprise 2,615,016 observations featuring 666,554 distinct firms from 1998 to 2008. This administrative data is collected and maintained by the National Bureau of Statistics and used to construct macroeconomic variables at different levels. This comprehensive dataset contains noise and error. Consistent with previous studies, we apply the following criteria to clean our initial sample.

1. We drop firm-years in which the values of important accounting variables are missing or abnormal (zero or negative values). The variables include total assets, output, book value of fixed assets, operating revenues, and number of employees. We also exclude firm-years in which the operating status is not reported as "Normal".

2. We drop firms in the utility sectors that have the four-digit industry codes 4400-4499 or 4600-4699.

3. We drop firm-years that report abnormal accounting values that contradict accounting principles. Specifically, we exclude firm-years in which
   - the amount of total debts does not equal the amount of short-term debt plus long-term debt, or any of the debt measures are negative;
   - the amount of current assets is larger than total assets;
   - the amount of fixed assets is larger than total assets;
   - the amount of the current depreciation is larger than the cumulative depreciation.

4. We drop firms that are smaller than a certain scale, as small firms may not have a reliable accounting system. Accordingly, we exclude firm-years in which
   - the number of employees is fewer than 30 or total wage expense is zero;
   - total assets are lower than CNY 5 million;
   - sales value is lower than CNY 5 million or sales per employee are lower than CNY 1,000; or
   - output value is lower than CNY 10,000 or output per employee is lower than CNY 1,000.

5. We drop firms that report incorrect or missing location codes. We drop firms with imprecise addresses that cannot be converted into coordinates using GIS techniques. We only keep firms that are located within 100 km of the borders of contiguous county-pairs.

The resulting sample consists of 407,342 firm-year observations, drawn from 119,229 distinct private firms. The county-pairs are constructed using the 2002 GIS map of China provided by the China Data Center, University of Michigan. After combining the data of each county-pair, we construct a sample that contains 1,864,513 observations at the county-pair, firm and year levels. In the sample, there are 164 industries, which are defined using the three-digit industry codes.

Appendix 3. Determinants of Minimum Wage Change

This table shows whether investment-related variables predict the occurrence of minimum wage changes. The dependent variable in the OLS regression is which is coded as a binary variable (1/0) with 1 representing a change in year $t+1$. To measure the county-level investment, we construct a size-weighted average of investment of all CIED firms located in the same county (*County Investment*), and a size-weighted average of capital to labor ratio of all CIED firms located in the same county (*County* $ln(K/L)$). We prefix *County Investment* and *County* $ln(K/L)$ by Δ to denote their corresponding growth rate. Macroeconomic control variables are measured at the level of city m that administers county c, and include the growth rate of GDP (ΔGDP), log value of GDP per capita ($ln(GDP\ per\ Capita)$), and growth rate of foreign direct investment (ΔFDI). County and province-by-year fixed effects are included. The robust standard errors are clustered at the county level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	$D_{t+1}^{\Delta MW}$			
$County\ Investment_t$	-0.003			
	[0.01]			
$County\ ln(K/L)_t$		0.003		
		[0.00]		
$\Delta County\ Investment_t$			0.000	
			[0.00]	
$\Delta County\ ln(K/L)_t$				-0.006
				[0.01]
ΔGDP_t	0.006	0.005	-0.005	0.001
	[0.01]	[0.01]	[0.01]	[0.01]
$\ln(GDP\ per\ Capita)_t$	0.005	0.005	0.016	0.007
	[0.01]	[0.01]	[0.01]	[0.01]
ΔFDI_t	0.001	0.001	0.000	0.001
	[0.00]	[0.00]	[0.00]	[0.00]
County FE	Y	Y	Y	Y
Province×Year FE	Y	Y	Y	Y
N	21,327	21,327	17,506	19,460
R^2	0.917	0.917	0.927	0.921

Table 1: Summary Statistics

The summary statistics for all regression variables are reported. The sample includes 407,342 firm-year observations with 119,229 distinct private Chinese manufacturing firms located within 100 km of the borders of contiguous county-pairs. Panel A presents the descriptive statistics of the firm-level dependent variables used in the analysis. $Investment$ is the change of net fixed assets from year t to $t+1$ plus current depreciation in year t, and then divided by total assets in year t. $ln(K/L)$ is the log value of net fixed assets divided by the number of employees. $Patent$ is the number of patent fillings by a firm in year t that are eventually granted. Long Leverage is long-term debts divided by assets. Long-term debt is defined as debts that mature beyond one year. $DebtStructure$ is long-term debts divided by total debt outstanding. $TotalLeverage$ is total debt scaled by assets. All main dependent variables in Panel A are measured in one year ahead of independent and control variables reported in Panels B and C. Panel B reports the county-level variables. After dropping missing observations in economic variables, the final sample includes 21,327 county-year observations and 2,330 unique counties with essential firm-level and regional variables in year t and $t+1$. MW, measured in thousands, is annualized minimum wage, defined as the monthly minimum wage in December multiplied by twelve. Other firm-year level variables are presented in Panel C. We consider two wage-related variables, the log value of average wage per employee, $ln(AW)$, and the log value of total wage expenditure, $ln(TW)$. The firm-level control variables include the log value of total assets, $ln(Assets)$; the ratio of net fixed assets over total assets, $Tangibility$; return to assets defined as profits divided by total assets, ROA; and sales growth rate from $t-1$ to t, $\Delta Sales$. The detailed variable definitions are given in Appendix 1.

Variables	N	Mean	S.D.	P25	Median	P75
Panel A. Main dependent variables at firm-year level (measured in year $t+1$)						
Investment	407,342	0.104	0.256	0.038	0.004	0.125
Investment1	407,342	0.061	0.221	0.007	-0.018	0.079
Investment2	407,342	0.119	0.293	0.034	0.003	0.13
ln(K/L)	407,342	4.333	0.991	3.709	4.363	4.99
Patent	407,342	0.171	2.803	0	0	0
Long Leverage	407,342	0.046	0.108	0	0	0.025
Debt Structure	406,540	0.08	0.173	0	0	0.049
Total Leverage	407,342	0.591	0.248	0.419	0.616	0.787
B. County-year Level Variables (measured in year t)						
MW	21,327	3.953	1.383	2.88	3.66	4.8
ln(MW)	21,327	1.317	0.338	1.058	1.297	1.569
C. Other Firm-year Level Variables (measured in year t)						
ln(AW)	407,342	2.515	0.521	2.201	2.525	2.821
ln(TW)	407,342	7.449	0.974	6.762	7.354	8.029
ln(Assets)	407,342	9.969	1.027	9.183	9.752	10.522
Tangibility	407,342	0.329	0.201	0.173	0.298	0.456
ROA	407,342	0.086	0.157	0.008	0.037	0.103
Δ Sales	407,342	0.343	0.707	-0.01	0.185	0.483

Table 2: Robustness for Baseline Regressions

This table presents the validity test for our empirical design. The results confirm that minimum wage policy has strongly influenced the firm level labor costs by regressing firm average wage and firm total wage on minimum wage $ln(MW)$. We define firm average wage, denoted by $ln(AW)$, as the log value of total wage expenditure divided by the number of employees, and firm total wage, denoted by $ln(TW)$, as the log value of total wage expenditure. The firm-level control variables include the log value of lagged total assets, $ln(Assets)$; a tangibility measure, $Tangibility$; and profitability measured by return on assets, ROA. The robust standard errors are clustered at the county level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dep. Vars.	$ln(AW)_t$		$ln(TW)_t$	
$ln(MW)_t$	0.505***	0.126***	0.160***	0.127***
	[0.03]	[0.03]	[0.06]	[0.04]
$ln(Assets)_t$	0.082***	0.092***	0.641***	0.461***
	[0.00]	[0.00]	[0.00]	[0.01]
$Tangibility_t$	-0.126***	-0.033***	-0.023	0.125***
	[0.01]	[0.01]	[0.02]	[0.01]
ROA_t	0.362***	0.366***	0.661***	0.698***
	[0.02]	[0.02]	[0.04]	[0.03]
Year FE	Y	Y	Y	Y
Province FE	Y	N	Y	N
Industry FE	Y	N	Y	N
Firm FE	N	Y	N	Y
N	407,342	407,342	407,342	407,342
R^2	0.364	0.708	0.511	0.876

Table 3: Baseline Regressions of the Effect of Minimum Wage on Investment

This table reports the baseline regression of corporate investment on minimum wage in samples of firms located within 100 km, 75 km, and 50 km of borders of contiguous county-pairs during the 1998-2008 period. County-pairs that straddle two provinces are excluded. The sample includes 4,205 unique county-pairs with essential firm-level information. Dependent variable, Investment, is the change of net fixed assets from year t to $t+1$ plus depreciation in year t scaled by total assets in year t. The main independent variable, $ln(MW)$, is the log value of annualized minimum wage. The firm-level control variables include the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, $Tangibility$; profitability measured by return on assets, ROA; and sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). All regression specifications have controlled for province-by-year, industry-by-year, county-pair, and firm fixed effects. The industry is based on three-digit industry classification. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** indicates the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Distance to the County Border	<100 km	<75 km	<50 km
Dep. Var.		$Investment_t + 1$	
$ln(MW)_t$	0.054***	0.056***	0.057***
	[0.02]	[0.02]	[0.02]
$ln(Assets)_t$	-0.209***	-0.207***	-0.201***
	[0.00]	[0.00]	[0.00]
$Tangibility_t$	-0.797***	-0.794***	-0.789***
	[0.01]	[0.01]	[0.01]
ROA_t	0.275***	0.274***	0.271***
	[0.01]	[0.01]	[0.01]
$\Delta Sales_t$	0.038***	0.038***	0.038***
	[0.00]	[0.00]	[0.00]
ΔGDP_t	0.044***	0.042***	0.053***
	[0.01]	[0.01]	[0.01]
$ln(GDPperCapita)_t$	-0.022**	-0.023**	-0.032***
	[0.01]	[0.01]	[0.01]
ΔFDI_t	-0.007***	-0.008***	-0.008***
	[0.00]	[0.00]	[0.00]
Province × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
County-pair FE	Y	Y	Y
Firm FE	Y	Y	Y
N	1,864,513	1,807,584	1,446,313
R^2	0.495	0.494	0.494

Table 4: Robustness for Baseline Regressions

This table reports several robustness checks for the baseline regression results reported in Table 3. Panels A and B report results estimated using alternative definitions of investments. The dependent variable in Panel A, $Investment1$, is defined as the change of net fixed assets from year t to $t+1$ without adding current depreciation in year t scaled by total assets in year t. The dependent variable in Panel B, $Investment2$, is defined as the change of original value of fixed assets from year t to $t+1$ scaled by total assets in year t. Panel C reports the results using a sample restricting to county pairs that both counties are administered by the same city. The estimated results from using a sample of state-owned enterprises (SOEs) and a sample of foreign firms are given in Panels D and E, respectively. The control variables in all panels are the same as Table 3 though not reported. All regression specifications have controlled for province-by-year, industry-by-year, county-pair, and firm fixed effects. The industry is based on three-digit industry classification. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** indicates the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Distance to the County Border	<100 km	<75 km	<50 km
Dep. Var.	Panel A. $Investment1_{t+1}$		
$ln(MW)_t$	0.022**	0.023**	0.027**
	[0.01]	[0.01]	[0.01]
N	1,864,513	1,807,584	1,446,313
R^2	0.501	0.5	0.5
Dep. Var.	Panel B. $Investment2_{t+1}$		
$ln(MW)_t$	0.066***	0.069***	0.062**
	[0.02]	[0.02]	[0.02]
N	1,864,513	1,807,584	1,446,313
R^2	0.458	0.457	0.457
Dep. Var.	Panel C. $Investment_{t+1} : Samecity$		
$ln(MW)_t$	0.049**	0.051**	0.042*
	[0.02]	[0.02]	[0.02]
N	1,253,900	1,231,453	1,054,689
R^2	0.5	0.499	0.499
Dep. Var.	Panel D. $Investment_{t+1}$: SOEs		
$ln(MW)_t$	0.085***	0.087***	0.085***
	[0.01]	[0.01]	[0.01]
N	692,587	677,038	571,983
R^2	0.513	0.511	0.51
Dep. Var.	Panel E. $Investment_{t+1}$: Foreign Firms		
$ln(MW)_t$	0.054***	0.056***	0.059***
	[0.02]	[0.02]	[0.02]
N	774,614	760,400	658,607
R^2	0.455	0.454	0.451
Firm and Economic Controls	Y	Y	Y
Province × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
County-pair FE	Y	Y	Y
Firm FE	Y	Y	Y

Table 5: Minimum Wage and the Capital-Labor Ratio

This table reports the analysis on the effect of minimum wage on the capital-labor ratio in the samples of firms located within 100, 75, and 50 km of the borders of contiguous county-pairs between 1998 and 2008. County pairs that straddle two provinces are excluded. The dependent variable, $ln(K/L)$, is defined as the log value of net fixed assets divided by the number of employees. $ln(MW)$, is the log value of annualized minimum wage. We include as control variables the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, $Tangibility$; profitability measured by return on assets, ROA; and growth opportunity measured by sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county, and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). All regression specifications have controlled for fixed effects at the province-by-year, industry-by-year, county-pair, and firm levels. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Distance to the County Border	<100 km	<75 km	<50 km
Dep. Var.		$ln(K/L)_{t+1}$	
$ln(MW)_t$	0.137***	0.137***	0.126***
	[0.03]	[0.03]	[0.03]
$ln(Assets)_t$	0.143***	0.144***	0.145***
	[0.00]	[0.00]	[0.00]
$Tangibility_t$	0.388***	0.393***	0.399***
	[0.01]	[0.01]	[0.01]
ROA_t	-0.056***	-0.059***	-0.071***
	[0.01]	[0.01]	[0.01]
$\Delta Sales$	-0.004***	-0.004***	-0.005***
	[0.00]	[0.00]	[0.00]
Economic Controls	Y	Y	Y
Province × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
County-pair FE	Y	Y	Y
Firm FE	Y	Y	Y
N	1,864,513	1,807,584	1,446,313
R^2	0.883	0.883	0.885

Table 6: Heterogeneous Effects of Minimum Wage: Conditional on Labor Intensity

This table reports the analysis on the effect of minimum wage on investment conditional on labor intensity. The sample consists of firms located within 50 km of the borders of contiguous county-pairs. County-pairs that straddle two provinces are excluded. Dependent variable, $Investment$, is the change of net fixed assets from year t to $t+1$ plus current depreciation in year t scaled by total assets in year t. The main independent variable, $ln(MW)$, is the log value of annualized minimum wage. We respectively proxy labor intensity by i) an industry-average ratio of total wage expenditure to total assets and ii) an industry-average ratio of total wage expenditure to sales. We sort all three-digit industries in our sample by each labor intensity measure, separately, and mark as "high intensity" those industries above sample median and as "low intensity" otherwise. We include as control variables the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, $Tangibility$; profitability measured by return on assets, ROA; and growth opportunity measured by sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county, and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). We report the p-value for the difference test that the null hypothesis states the estimated coefficients of $ln(MW)$ in two subsamples not significantly different. All regression specifications have controlled for fixed effects at the province-by-year, industry-by-year, county-pair, and firm levels. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Distance to the County Border	<50 km			
Dep. Var.	$Investment_{t+1}$			
	Labor Intensity: Wage/Assets		Labor Intensity: Wage/Sales	
	High	Low	High	Low
$ln(MW)_t$	0.104***	0.027	0.083***	0.036
	[0.03]	[0.02]	[0.02]	[0.02]
$ln(Assets)_t$	-0.198***	-0.211***	-0.188***	-0.222***
	[0.00]	[0.00]	[0.00]	[0.00]
$Tangibility_t$	-0.776***	-0.819***	-0.774***	-0.823***
	[0.01]	[0.01]	[0.01]	[0.01]
ROA_t	0.275***	0.266***	0.273***	0.271***
	[0.01]	[0.01]	[0.01]	[0.01]
$\Delta Sales_t$	0.039***	0.038***	0.037***	0.039***
	[0.00]	[0.00]	[0.00]	[0.00]
H0 : (1) = (2)	p = 0.00			
H0 : (3) = (4)			p = 0.00	
Economic Controls	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
County-pair FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	752,709	693,604	743,418	702,895
R^2	0.506	0.505	0.506	0.506

Table 7: Heterogeneous Effects of Minimum Wage: Conditional on Industry Competition

This table reports the analysis on the effect of minimum wage on investment conditional on industry competition. The sample consists of firms located within 50 km of the borders of contiguous county-pairs. County-pairs that straddle two provinces are excluded. Dependent variable, $Investment$, is the change of net fixed assets from year t to $t+1$ plus current depreciation in year t scaled by total assets in year t. The main independent variable, $ln(MW)$, is the log value of annualized minimum wage. We use two industry competition measures. The first is based on the Herfindahl Hirschman Index (HHI) of market shares in terms of sales for all firms within a three-digit industry. The second measure follows Aghion et al. (2005) and is based on Lerner Index, which is the ratio of operating profits minus capital costs to sales. We sort all three-digit industries in our sample by each competition measure, separately, and mark as "high competition" those industries below median HHI (below median Lerner Index) and those industries above median HHI (above median Lerner Index) as "low competition". We include as control variables the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, $Tangibility$; profitability measured by return on assets, ROA; and growth opportunity measured by sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county, and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). We report the p-value for the difference test that the null hypothesis states the estimated coefficients of $ln(MW)$ in two subsamples not significantly different. All regression specifications have controlled for fixed effects at the province-by-year, industry-by-year, county-pair, and firm levels. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Distance to the County Border	<50 km			
Dep. Var.	$Investment_{t+1}$			
	Labor Intensity: Wage/Assets		Labor Intensity: Wage/Sales	
	High	Low	High	Low
$ln(MW)_t$	0.063***	0.037	0.078***	0.036
	[0.02]	[0.03]	[0.02]	[0.02]
$ln(Assets)_t$	-0.201***	-0.221***	-0.207***	-0.203***
	[0.00]	[0.00]	[0.00]	[0.00]
$Tangibility_t$	-0.785***	-0.846***	-0.800***	-0.796***
	[0.01]	[0.01]	[0.01]	[0.01]
ROA_t	0.271***	0.273***	0.275***	0.264***
	[0.01]	[0.01]	[0.01]	[0.01]
$\Delta Sales_t$	0.039***	0.035***	0.039***	0.036***
	[0.00]	[0.00]	[0.00]	[0.00]
H0 : (1) = (2)	p = 0.05			
H0 : (3) = (4)			p = 0.00	
Economic Controls	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
County-pair FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	1,148,477	297,836	888,939	557,374
R^2	0.497	0.543	0.5	0.516

Table 8: Heterogeneous Effects of Minimum Wage: Conditional on Access to Finance

This table reports the analysis of the effect of minimum wage on investment, conditional on access to finance. The sample consists of firms located within 50 km of the borders of contiguous county-pairs. The dependent variable, $Investment$, is the change of net fixed assets from year t to $t+1$ plus current depreciation in year t scaled by total assets in year t. The main independent variable, $ln(MW)$, is the log value of annualized minimum wage. We measure a firm's access to credit by local bank branch density, which is defined as the number of commercial bank branches in a city scaled by the city's total population in a year. We sort all cities in our sample by bank branch density and label cities above median density as "high bank density" and as "low bank density" otherwise. We restrict the sample to county pairs in which both counties in a pair are administered by a same city. We include as control variables the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, $Tangibility$; profitability measured by return on assets, ROA; and growth opportunity measured by sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county, and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). We report the p-value for the difference test that the null hypothesis states is the estimated coefficients of $ln(MW)$ in two subsamples not significantly different. All regression specifications have controlled for fixed effects at the province-by-year, industry-by-year, county-pair, and firm levels. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
Distance to the County Border	<50 km	
Dep. Var.	$Investment_t + 1$	
	High	Low
$ln(MW)_t$	0.075**	0.002
	[0.03]	[0.06]
$ln(Assets)_t$	-0.177***	-0.238***
	[0.00]	[0.01]
$Tangibility_t$	-0.741***	-0.860***
	[0.01]	[0.01]
ROA_t	0.234***	0.319***
	[0.01]	[0.01]
$\Delta Sales_t$	0.035***	0.040***
	[0.00]	[0.00]
H0 : (1) = (2)	p = 0.00	
Economic Controls	Y	Y
Province × Year FE	Y	Y
Industry × Year FE	Y	Y
County-pair FE	Y	Y
Firm FE	Y	Y
N	697,907	356,662
R^2	0.501	0.51

Table 9: Heterogeneous Effects of Minimum Wage: Conditional on Legal Environment

This table reports the analysis of the effect of minimum wage on investment conditional on legal environment. The sample consists of firms located within 50 km of the borders of contiguous county-pairs. County-pairs that straddle two provinces are excluded. Dependent variable, $Investment$, is the change of net fixed assets from year t to $t+1$ plus current depreciation in year t scaled by total assets in year t. The main independent variable, $ln(MW)$, is the log value of annualized minimum wage. We measure legal environment by the legal infrastructure development index in 1997, developed by Fan and Wang (2006). We sort all provinces in our sample by the index, and mark as "high" those above the median index and as "low" otherwise. We include as control variables the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, $Tangibility$; profitability measured by return on assets, ROA; and growth opportunity measured by sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county, and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). We report the p-value for the difference test that the null hypothesis states is the estimated coefficients of $ln(MW)$ in two subsamples not significantly different. All regression specifications have controlled for fixed effects at the province-by-year, industry-by-year, county-pair, and firm levels. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
Distance to the County Border	<50 km	
Dep. Var.	$Investment_t + 1$	
	High	Low
$ln(MW)_t$	0.173***	-0.021
	[0.04]	[0.02]
$ln(Assets)_t$	-0.179***	-0.218***
	[0.01]	[0.01]
$Tangibility_t$	-0.744***	-0.819***
	[0.01]	[0.01]
ROA_t	0.248***	0.281***
	[0.02]	[0.01]
$\Delta Sales$	0.035***	0.040***
	[0.00]	[0.00]
H0 : (1) = (2)	p = 0.00	
Economic Controls	Y	Y
Province × Year FE	Y	Y
Industry × Year FE	Y	Y
County-pair FE	Y	Y
Firm FE	Y	Y
N	600,158	846,155
R^2	0.486	0.503

Table 10: Minimum Wage and Corporate Innovation

This table reports the analysis on the effect of minimum wage on corporate innovation in the samples of firms located within 100, 75, and 50 km of the borders of contiguous county-pairs between 1998 and 2008. County-pairs that straddle two provinces are excluded. We measure corporate innovation by patent count, which is defined as the log value of one plus the number of number of granted patents applied by a firm in a year. The main independent variable, ln(MW), is the log value of annualized minimum wage. We include as control variables the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, $Tangibility$; profitability measured by return on assets, ROA; and growth opportunity measured by sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county, and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). All regression specifications have controlled for fixed effects at the province-by-year, industry-by-year, county-pair, and firm levels. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Distance to the County Border	<100 km	<75 km	<50 km
Dep. Var.		$ln(1 + Patent)_t + 1$	
$ln(MW)_t$	0.022**	0.025**	0.031**
	[0.01]	[0.01]	[0.01]
$ln(Assets)_t$	0.036***	0.036***	0.037***
	[0.00]	[0.00]	[0.00]
$Tangibility_t$	0.011***	0.012***	0.012***
	[0.00]	[0.00]	[0.00]
ROA_t	0.019***	0.019***	0.020***
	[0.00]	[0.00]	[0.00]
$\Delta Sales_t$	0.003***	0.003***	0.003***
	[0.00]	[0.00]	[0.00]
Economic Controls	Y	Y	Y
Province × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
County-pair FE	Y	Y	Y
Firm FE	Y	Y	Y
N	1,864,513	1,807,584	1,446,313
R^2	0.58	0.58	0.585

Table 11: Minimum Wage and Firm Leverage

This table reports the baseline regression estimates of the effect of minimum wage on firm leverage in the samples of firms located within 100, 75, and 50 km of the borders of contiguous county-pairs between 1998 and 2008. County-pairs that straddle two provinces are excluded meaning all firms in a county-pair are located in the same province. We employ three firm leverage metrics, which are *Long Leverage*, defined as long-term debts divided by assets; *Debt Structure*, as long-term debts divided by total debts outstanding; and *Total Leverage*, as total debts outstanding divided by total assets. The main independent variable, $ln(MW)$, is the log value of annualized minimum wage. All control variables are suppressed due to space constraint. We include as control variables the log value of lagged total assets, $ln(Assets)$; a lagged tangibility measure, *Tangibility*; profitability measured by return on assets, ROA; and growth opportunity measured by sales growth, $\Delta Sales$. Macroeconomic variables are measured at the level of cities that administer the relevant county, and include the growth rate of GDP (ΔGDP), the log value of GDP per capita ($ln(GDP\ per\ Capita)$), and foreign direct investment growth (ΔFDI). All regression specifications have controlled for fixed effects at the province-by-year, industry-by-year, county-pair, and firm levels. The robust standard errors are clustered at the county-pair level and reported in brackets. *, **, and *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Distance to the County Border	<100 km	<75 km	<50 km
Dep. Var.		Panel A. $Long\ Leverage_{t+1}$	
$ln(MW)_t$	0.021***	0.022***	0.024***
	[0.00]	[0.00]	[0.00]
N	1,864,513	1,807,584	1,446,313
R^2	0.678	0.677	0.676
Dep. Var.		Panel B. $Debt\ Structure_{t+1}$	
$ln(MW)_t$	0.029***	0.029***	0.033***
	[0.01]	[0.01]	[0.01]
N	1,861,245	1,804,549	1,444,127
R^2	0.671	0.671	0.671
Dep. Var.		Panel C. $Total\ Leverage_{t+1}$	
$ln(MW)_t$	0.007	0.008	0.004
	[0.01]	[0.01]	[0.01]
N	1,864,513	1,807,584	1,446,313
R^2	0.808	0.808	0.809
Firm and Economic Controls	Y	Y	Y
Province × Year FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
County-pair FE	Y	Y	Y
Firm FE	Y	Y	Y

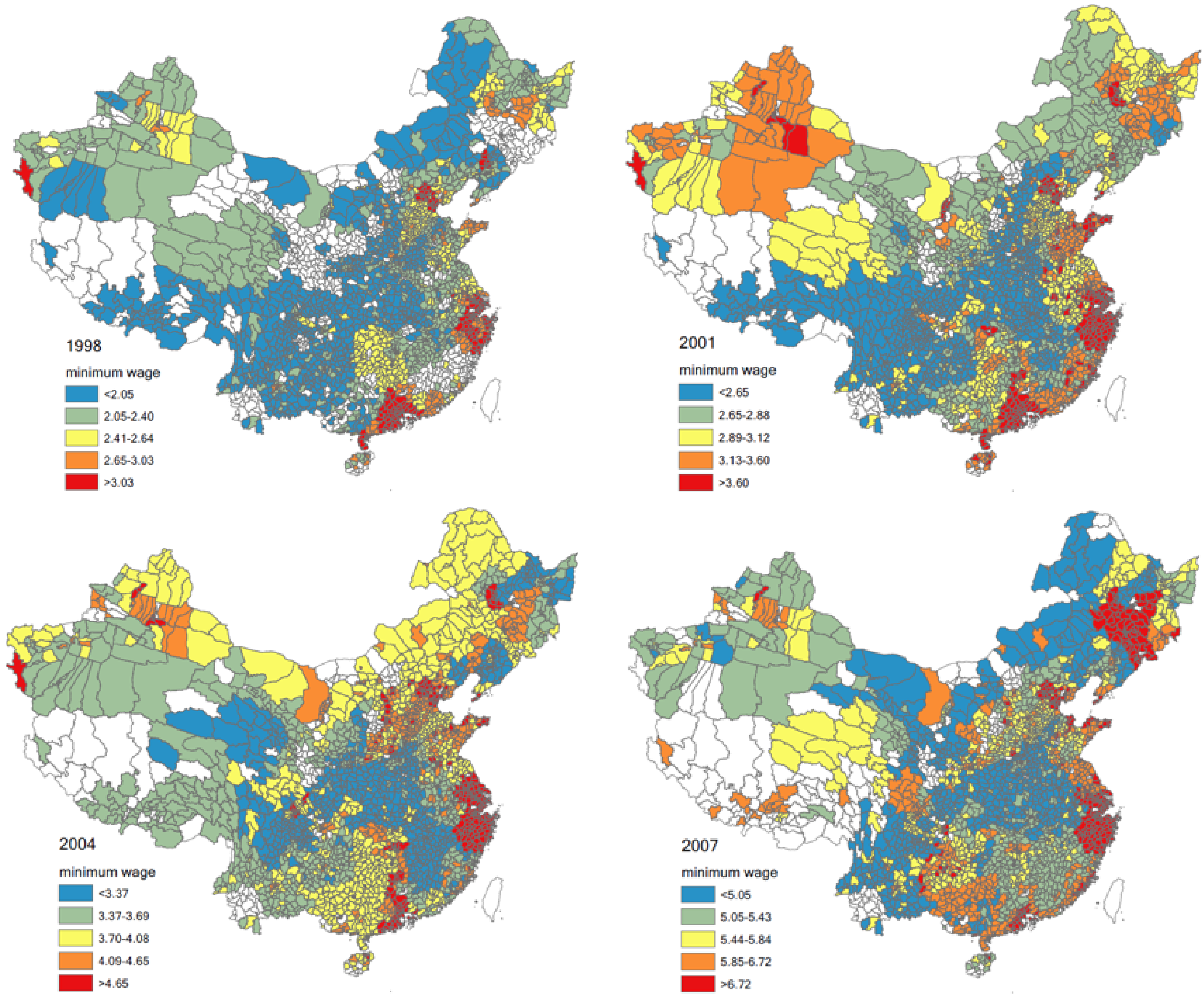

Figure 1: Spatial Distribution of Minimum Wage in China

This figure plots four diagrams for the distribution of county-level minimum wage in China, with each diagram representing a different sample year. In each diagram, we sort all Chinese counties into quintiles according to their minimum wages and assign each quintile with a different color, with blue corresponding to the first quintile, green to the second quintile, yellow to the third quintile, orange to the fourth quintile, and red to the fifth quintile.

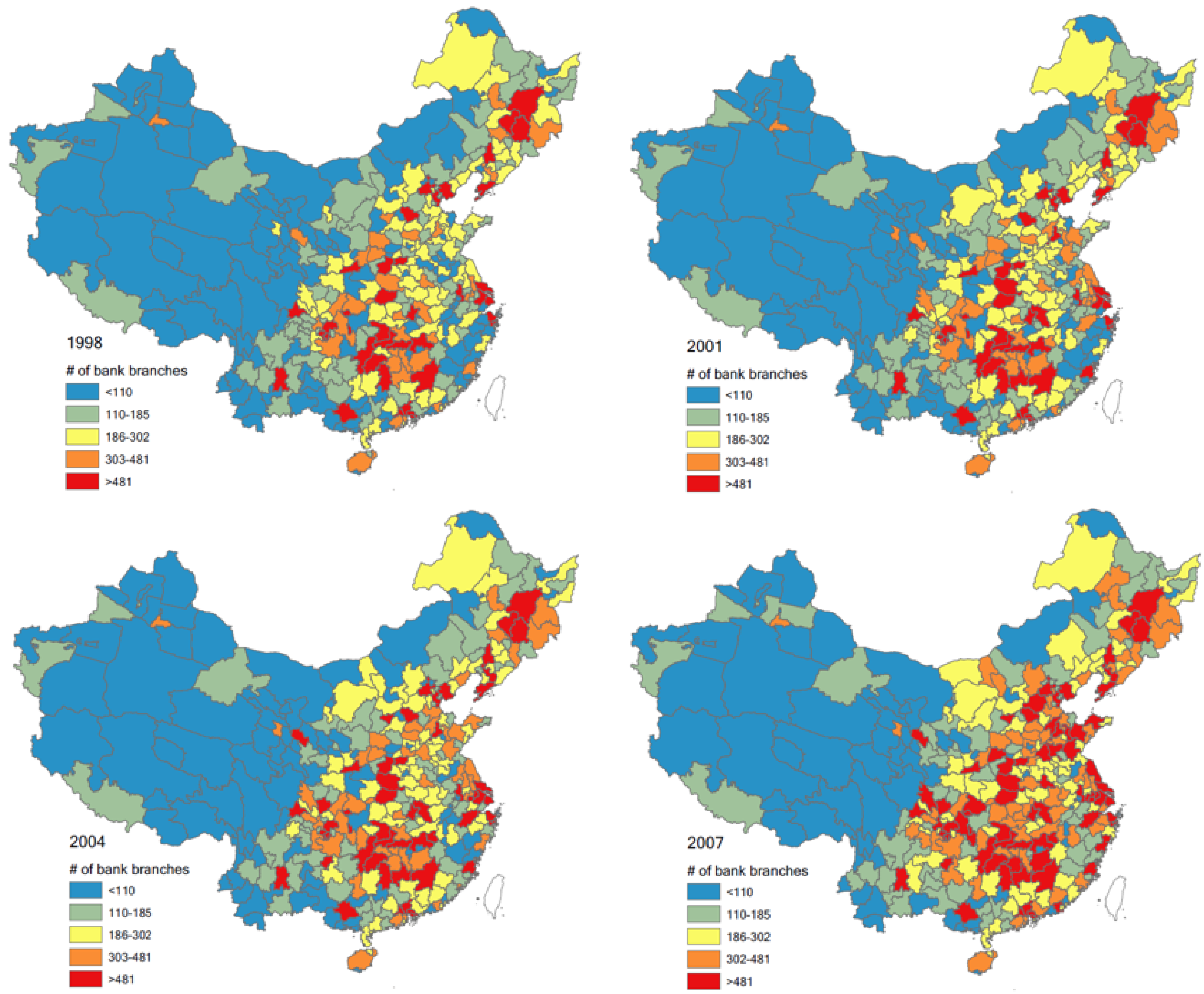

Figure 2: Spatial Distribution of Commercial Bank Branches in China

This figure plots four diagrams for the distribution city-level commercial bank branch count in China, with each diagram representing a different sample year. In each diagram, we sort all cities into quintiles according to their commercial bank branches counts and assign each quintile with a different color, with blue corresponding to the first quintile, green to the second quintile, yellow to the third quintile, orange to the fourth quintile, and red to the fifth quintile.