Property Rights, Labor Supply, and Firm Capital Structure

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Abstract

We examine how increased labor supply in the local labor market where firms operate affects their capital structure decisions. We exploit China's land titling program as a quasi-natural experiment to analyze how private and publicly traded firms respond to an abrupt increase in labor supply. We construct labor market areas in China using the inter-city commuting patterns observed in the Baidu Qianxi data from 2023. Our findings indicate that the reform leads to an increase in the debt-to-capital ratio of public firms, while private firms experience a decrease in their debt-to-capital ratio. These results shed light on the interplay between labor market frictions and financial flexibility in capital structure decisions. The entitlement of property rights to households stimulates labor supply, reducing the cost of job loss and alleviating labor market frictions. This, in turn, can reduce firms' indirect costs of financial distress and increase their leverage. However, firms also choose to lower their leverage to maintain financial flexibility and attract workers in the local labor market. The former effect is more pronounced in public firms, while the latter effect is more prominent in private firms.

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1 Introduction

In recent decades, labor has become an increasingly important factor in the success of business. Graham (2022) finds that firms adopting a stakeholder-centric perspective prioritize employees as the primary stakeholder for the organization's success. As the workforce becomes a central focus for modern firms, there has been a growing body of research aiming to explain the relationship between labor market outcomes and corporate finance decisions. These studies reveal that labor market search friction has a significant impact on firms' capital structure (e.g., Agrawal and Matsa, 2013; Bronars and Deere, 1991; Matsa, 2010; Sanati, 2022). More specifically, Kim (2020) examines the effect of a sudden increase in labor demand resulting from a large plant opening and find that firms operating in larger local labor markets tend to significantly increase their leverage. However, when the size of a local labor market experiences an abrupt increase due to a labor supply shock, what factors might account for the association between labor market size and firms' capital structure?

In this paper, we examine how the increased labor supply in the local labor markets where firms operate affects their capital structure decisions. To do so, we employ China's land titling program as an exogenous shock to investigate how private and publicly traded firms respond to an abrupt increase in labor supply. To establish the theoretical link between the labor market and capital structure, we refer to the modified trade-off theory proposed by Titman (1984) and Berk et al. (2010), as well as a novel model of capital structure and labor outcomes developed by Liu (2019). The rationale is that an expected increase in labor supply can reduce the cost of labor. Moreover, larger labor markets can alleviate the costs associated with job loss by facilitating workers in finding employment opportunities. This implies that firms operating in larger labor markets with an increased labor supply may increase their leverage, as the marginal compensating premium required for increased risk of job loss tends to be smaller. Another competing factor is the "strategic benefit" of debt in wage negotiation and the cost of hiring. An increased labor supply suggests a decrease in workers' bargaining power, which discourage firms from using higher leverage. Furthermore, an increased labor supply can lead to heightened competition. Low leverage can encourage the workforce to apply for potential job vacancies, as it reduces the potential ex-post bankruptcy cost for employers.

The key difference between private and publicly traded firms that we emphasize in this paper is that publicly traded firms tend to use more external financing and respond more to exogenous shock due to their broader access to external financing and lower borrowing costs, consistent with Phillips and Sertsios (2014). If this is the case, publicly traded firms are expected to use more debt to take advantage of the lower cost of labor and financial distress. On the other hand, when competing with their public counterparts, private firms are expected to decrease their leverage to satisfy their greater demand of financial flexibility and increase the matching probability in the labor market.

We begin our analysis by constructing local labor markets in China. A delineation for labor markets using state or prefecture borders fails to accurately represent the relationship between place of work and residence. Following the approach of Tolbert and Sizer (1996) and Tolbert and Killian (1987), we utilize Baidu Qianxi (Baidu Mobility) migration data from 1 January 2023 to 12 February 2023 and a hierarchical agglomerative clustering method to create 74 local market areas in China. The Baidu Qianxi data provide valuable insights into the large-scale population movement during the Spring Festival, a prominent traditional holiday. Unlike previous studies that use census or survey data, the Baidu Qianxi data can be useful in capturing journey-to-work patterns. This is because during Spring Festival travel rush, commonly known as "chunyun", millions of individuals travel back to their hometowns to reunite with their families and travel to their working cities after the holiday.

We test our hypotheses by exploiting China's staggered introduction of the land titling program as our empirical identification strategy. The land titling reform is expected to have a significant effect in the local labor market. Historically, property rights over rural land in China have been established through continuous personal use rather than through land titles. The lack of a formal titling process results in incomplete and ambiguous land property rights, leading to numerous land disputes. This system hinders labor mobility by discouraging individuals from leaving their land unused or in the hands of others, as it could result in the loss of their property rights (De Janvry et al., 2015). The introduction of clear land property rights under the land titling reform provides rural households greater possibilities to seek employment in more developed cities other than land-dependent in their hometowns.

We implement a staggered difference-in-differences approach (DiD) and find that private firms in treated local labor markets decrease their leverage, defined as total debt (long-term plus short-term debt) divided by the sum of the book value of equity and total debt. On the other hand, publicly traded firms in treated local labor markets increase their leverage compared to those in untreated local labor markets. This result is robust to a variety of control variables and fixed effects, including firm, local labor market, year, and industry-by-year fixed effects. To ensure the parallel trends assumption holds in the pre-treatment periods, we conduct dynamic regression analyses and provide valid measures of the impact of the land titling reform on firm leverage.

Next, we examine the mechanisms that drive the effects of the land titling reform on leverage of private and public firms. We begin by documenting that the reform has a significantly positive impact on the number of laborers in each city within the local labor markets. This supports our hypothesis that the land titling reform can lead to a shock of labor supply in the local labor market. Consistent with reform being able to increase labor supply and reduce the cost of labor and financial distress, we find a significant reduction in wages of private and public firms. However, we only find a significant increase in the number of employees for private firms. This finding, coupled with our baseline results, suggests that private firms prioritize financial flexibility and reduce their leverage, despite the lower cost of labor. Additionally, the low leverage allows them to attract new workers in the competitive local labor markets. On the other hand, we do not find significant change in the number of employees for publicly traded firms. This insignificant employee change combined with the significant wage decrease and our baseline results, suggests that publicly traded firms take advantage of the reduced cost of labor for incumbent employees and increase their leverage after the reform.

To better understand the dynamics of how characteristics of cities and firms moderate firms' capital structure decisions, we examine the cross-sectional heterogeneity. First, we analyze the city-level heterogeneity. We find that the decrease in private firms' leverage and the increase in public firms' leverage are only significant in firms operating in the labor import cities. Additionally, we examine the interactions among four firm-level characteristics including ownership, firm size, financial constraint, and investment focus. We find that the results are more pronounced for small non-SOE private firms that are financially constrained and more labor intensive. Similarly, the results are more pronounced for SOE listed firms that are financially constrained and more labor intensive. These results are intuitive and align with our baseline results.

The main contribution of this paper is to provide evidence that increased labor supply in the local labor markets can shape firms' capital structure. Our paper contributes to a burgeoning literature that documents the interaction between the labor market and capital structure. Most of this literature examines how local labor laws affect labor and firm outcomes. Agrawal and Matsa (2013) use state-level changes in unemployment insurance benefit to show that employee benefits can affect firm's capital structure decisions. Sanati (2022) finds that an increase in labor mobility leads to a decrease in firms use of debt and investment rates. Serfling (2016) exploits the adoption of labor protection laws and suggests that the increased employee firing cost can reduce firms' debt ratios. Al-Sabah and Ouimet (2021) document an increase in employment following the implementation of a paid sick leave policy.

We add to this literature by examining the impact of the land titling reform on firms' use of debt. While the land titling reform may not be directly related to labor laws, understanding its influence firms' financial decisions can shed light on the role of land property rights. In this paper, we suggest that land property rights cause labor reallocation in rural areas, as individuals move from their own land-based agriculture activities to urban areas in search of job opportunities. This shift in the labor market increases the workforce in the local labor market, subsequently influencing firms' capital structure decisions. We also provide complementary empirical evidence to the theoretical frameworks on the relationship between the labor market and capital structure (Berk et al., 2010; Liu, 2019; Matsa, 2018; Titman, 1984).

We also contribute to the literature that investigates the differential financing patterns between private and publicly traded firms. Existing studies have shown that private and public firms have different financing frequencies (e.g., Brav, 2009). Phillips and Sertsios (2014) utilize the Medicare national coverage reimbursement program and find that private firms obtain external financing much less frequently than public firms. They suggest that private and publicly traded firms respond differently to changes in investment opportunities. We add to this literature by showing that private and publicly traded firms also have distinct reactions to changes in the local labor market. We further connect these differential financing decisions to capital structure trade-off theory (Berk et al., 2010; Liu, 2019; Titman, 1984) and financial flexibility theory (DeAngelo and DeAngelo, 2007).

Finally, this paper contributes to the existing literature on property rights and economic development. It is widely accepted by economists that the establishment of enhanced property rights by institutions lead to positive economic outcomes. Previous studies primarily emphasize the effect on household wealth. Acemoglu et al., 2001 suggested that property rights play an important role in explaining the variations in income per capita across countries. Field (2007) documented the effect of property rights on the household-level labor outcomes. We complement this literature by providing evidence of the effect on firm-level outcome. Firms are a significant driver of economic development, and understanding how property rights impact their decisions is crucial. an increase in labor supply resulting from the land titling program leads to private firms reducing leverage to attract more job seekers. Consequently, these firms have a larger number of employees following the reform, contributing to a reduction in the unemployment rate within the local labor market. This suggests that property rights play a critical role in fostering employment growth for firms and local areas.

The remainder of this paper is organized as follows. We discuss the institutional background of the land titling reform and theory in Section 2. We discuss data sources in Section 3. We report the baseline results in Section 4. We report the cross-level heterogeneity results in Section 5. We conclude in Section 6.

2 Institutional Background, Theory, and Hypotheses Development

2.1 Land reform history and land titling program in China

Prior to 1949, private land ownership was common in China and land transactions occurred frequently. A household's wealth was directly linked to the amount of land it owned. Since the establishment of the People's Republic of China in 1949, China has launched four major farmland reforms to improve land-use efficiency, to rationalize land allocation, and to coordinate urban and rural development.

2.1.1 Land reform history

The first reform, in the early 1950s, confiscated land from landlords and distributed it to landless peasants, allowing them to own their own land. The second reform, in the mid-1950s, was a campaign of collectivization which compelled individual farmers to join collectives, leading to the establishment of the People's Commune. By 1958, all land was either state- or collectively owned and was considered a commodity and had no value (Ding, 2003). Characterized by centrally controlled property rights and a misapplied egalitarian principle of distribution, this system destroyed farmers' operational freedom and enthusiasm for production, resulting in the poor performance (Hu et al., 2023). Therefore, land-use systems in China have gradually evolved over the last four decades. Following China's adoption of "open door" policy in 1979, the third reform introduced a family-based contract system known as the household responsibility system (HRS), which successfully separated land ownership and contract rights. Under this system, land in a village was owned by the village collective, but farmers held the contract rights and could farm the land themselves or relinquish their contract rights to others. Given that operational rights were not explicitly defined, the village collectives had the right to distribute and adjust land allocations for public use, infrastructure or other purposes (Bu and Liao, 2022).

The HRS for farmland reform achieved remarkable results, but its equal distribution of land and effects on land tenure security had negative impacts on economic development (Deininger and Jin, 2009). First, the short duration of land leases offered poor land tenure security to rural households, discouraging land-improving investments. The initial land contracts between rural households and their village collective lasted for 15 years in the early stages of the HRS, and were later extended to 30 years after the expiration of the first 15-year contracts in 1997. A survey by Schwarzwalder et al. (2002) shows that despite around 60% of households having received written land use contracts, only 13% of the contracts prohibited future land readjustment, while 25% explicitly permitted it, and the remainder was ambiguous on whether such measures were possible. This resulted in only 12% of farmers feeling secure in their land against further readjustment, which could have an impact on their willingness to invest in higher value crops. Furthermore, periodic reallocations of land by village authorities threaten land tenure security. To distribute land based on household size and past labor decisions, communities often adopt labor-contingent land access and frequent reallocations, which impose conditions on labor use and create distorted incentives for households to oversupply labor to agriculture (De Janvry et al., 2015). This results in small-scale, decentralized, and fragmented farming, often leading to abandoned or low productivity land (Vendryes, 2010).

2.1.2 Land titling program in China

In recent years, the Chinese government has implemented the Land Certification Program to enhance land tenure security for rural households. Starting from 2008, China launched a fourth land reform by initiating a series of pilot projects for land titling programs (LTP) via Document No. 1 of the Central Committee of the Communist Party of China. The Ministry of Agriculture selected villages and towns from eight provinces, including Shandong, Sichuan, Hunan, Chongqing, Guangdong, Guangxi, Heilongjiang, and Jiangxi, as pilot samples for the implementation of LTP in 2008. In March 2011, the program was expanded nationwide by the Ministry of Agriculture and six other departments. Subsequently, Document No. 1 continued to stress the significance of the LTP and aimed to achieve national coverage by 2019 by expanding to more provinces (Bu and Liao, 2022).

The LTP differs from previous land reforms in multiples ways. First, it consolidated the collective membership identity, granting farmers stable and assured land property rights, and encouraging their participation in land transfers. Second, it implemented a "four boundaries" policy that demarcated clear land boundaries, thus better maintaining farmers' benefits (Deininger et al., 2011; Luo, 2018). Third, LTP separated land operational rights from land contract rights and provides ownership, contract, and operational rights to farmers, known as the three-rights division, which were previously only partial guarantees for ownership and contracts without access to credit or the ability to sell land. Additionally, a pilot program allowing the mortgage of land operational rights has been initiated, making operating land a more attractive prospect (Bu and Liao, 2022).

2.2 Theoretical link between labor market and capital structure

The way a firm's capital structure adjusts following the land titling reform can be affected by several factors. The first factor is whether LTP affects the local labor market. Property rights over rural land in China have historically been maintained through continuous personal use rather than through land titles. The absence of a formal titling process creates incomplete and ambiguous land property rights, leading to numerous land disputes. This system restricts labor mobility by discouraging individuals from leaving their land idle or in the hands of others, as it could result in the loss of their property rights (De Janvry et al., 2015). The establishment of clear land property rights under LTP offers rural households greater possibilities for transitioning from own-land-based activities and migrating from their hometowns to seek employment.

Assuming that LTP is effective, there may be an expected increase in labor supply in the local labor market. The second factor that can influence a firm's capital structure choices is the interaction between the labor market and capital structure decisions. Titman (1984) and Berk et al. (2010) modify the traditional trade-off theory of capital structure to include labor market frictions. In this model, leverage makes unemployment costly for firms, as they need to provide higher compensation for employees due to the increased likelihood of financial distress and layoffs (Matsa, 2018). However, in markets with a larger labor supply, the costs associated with job loss are reduced by facilitating workers in their job search (Petrongolo and Pissarides, 2006). In such markets, the marginal compensating premium required for increased risk of job loss, known as the indirect costs of financial distress, is smaller when firms use more debt (Agrawal and Matsa, 2013). Moreover, an increase in labor supply suggests a decrease in the cost of labor. A reduction in the cost of labor, coupled with the lower indirect costs of financial distress suggests that a firm in a local labor market that implements LTP may use more debt in their capital structure.

Liu (2019) introduces a novel model of capital structure policies in a frictional labor market that does not rely on the tax benefit of debt from the traditional capital structure. In this model, firms face a trade-off between the "strategic benefit" of debt in wage negotiations and the cost of debt in labor hiring. An increase in the labor supply suggests a decrease in workers' bargaining power. This may discourage employers from using higher leverage, known as strategic debt, which grants them an advantage during wage negotiations (e.g., Agrawal and Matsa, 2013; Bronars and Deere, 1991; Matsa, 2010). Additionally, an increase in the labor supply implies increased competition for labor. Brown and Matsa (2016) document that job seekers accurately perceive firms' financial condition. Thus, an increase in an employer's distress can lead to fewer and lower quality applicants. Lower leverage, which reduces the potential post-match bankruptcy cost for employers, can encourage job seekers from applying for the potential vacancies, thus increasing employers' matching probability in the labor market. This may reduce the cost of their hiring probability (Liu, 2019). Assuming a reduction in workers' bargaining power and increased labor market competition, a firm in a local labor market that implements LTP may use less debt in their capital structure.

2.3 Financing decisions between private and publicly traded firms

How private and publicly traded firms adjust their capital structures in response to land titling reform can be influenced by how their differing sensitivities to external financing. Due to their broader access to external financing, publicly traded firms may have an advantage in raising funds compared to private firms and respond more to exogenous changes. Similarly, Phillips and Sertsios (2014) find that private firms tend to use less external financing than publicly traded firms. Moreover, publicly traded firms typically have greater borrowing-cost bargaining power, resulting in lower borrowing expenses (Saunders and Steffen, 2011). Consequently, a publicly traded firm in a local labor market implementing LTP may use more debt to take advantage of the lower cost of labor and the indirect costs of financial distress.

Financial flexibility may also need to be considered in our study. DeAngelo and DeAngelo (2007) suggested that financial flexibility is a critical missing link in the traditional capital structure theory. Empirical evidence has shown how the demand for financial flexibility can influence firms' capital structure decisions (e.g., Byoun, 2011; Clark, 2010; Denis and McKeon, 2012). Developing firms that are in the phase of financial flexibility building tend to have low leverage, while firms that are in the process of utilizing or recharging financial flexibility tend to have moderate to high leverage. The demand for increasing financial flexibility that helps to retain the workforce against labor mobility has been observed in firms relying on skilled workers (Sanati, 2022). Brav (2009) found that private firms heavily rely on debt financing and tend to have high leverage ratios due to their limited access to other financing sources. Assuming an attempt to maintain their financial flexibility and increase the matching probability in the labor market while competing with their public counterparts, a private firm in a local labor market that implements LTP may use less debt.

3 Data

3.1 Labor market areas

U.S. labor studies have created distinct geographic schemas used to represent labor market areas, which are seen as the relationships between employers and workers. These relationships exist within the boundaries of places of work and residence. Therefore, a spatial approach using state or prefecture borders as a delineation for labor markets is unsatisfactory as it fails to represent these relationships. Some studies relied on metropolitan area definitions such as Metropolitan Statistical Areas (MSAs) that use an urban center and its surrounding counties as a labor market. However, this approach excludes nonmetropolitan places by definition.

U.S. researchers are increasingly adopting commuting zones (CZs) proposed by Tolbert and Sizer (1996) and Tolbert and Killian (1987) over traditional administrative units such as states and counties. CZs represent integrated economic units formed by commuting across multiple administrative boundaries. Tolbert and Sizer (1996) utilized the hierarchical agglomerative clustering (HAC) method and 1990 Census journey-to-work data to delineate 741 CZs and 394 LMAs.[1] Daisuke et al. (2020) utilized the same method and construct 265 CZs in Japan. Similarly, Bishop et al. (2021) construct 291 LMAs in Australia.

To delineate labor market areas in China, we apply Tolbert and Sizer (1996)'s HAC method using Baidu Qianxi (Baidu Mobility) migration data from 1 January 2023 to 12 February 2023. Baidu Qianxi data, derived from Baidu Map's location-based service (LBS), was initially designed to capture the significant population movement during the Spring Festival, a major traditional holiday in China. The Spring Festival travel rush, also known as "chunyun", refers to the nationwide peak of traffic when millions of passengers return to their hometowns before the Chinese Lunar New Year to reunite with their families and travel to their working cities after the holiday. "Chunyun" typically lasts for 40 days, with 15 days before and 25 days after the Spring Festival. This phenomenon has been widely studied in literature for analyzing population flow (e.g., Weiwen (2008); Jia et al. (2020)).

Baidu Qianxi provides two relevant daily datasets: a relative traffic volume index (V_i), which is a linearly scaled number of the daily traffic outflow or inflow from a city, and the proportions (P_{ij}) of the traffic heading towards or coming from various destinations. Therefore, the daily relative traffic volume from city i to city j can be calculated as $V_i P_{ij}$ (Fisman et al., 2021; Liu et al., 2022; Yang and Xie, 2020). P_{ij} is only available from 2020 Spring Festival to 2023 Spring Festival. Figure A.1 illustrates the traffic flow from Baidu Qianxi using Shanghai as an example.[2] Panel A depicts the traffic outflow from Shanghai on the first date of the 2023 Spring Festival, while Panel B presents the traffic inflow to Shanghai on the final date of the 2023 Spring Festival. Notably, there are observable similarities in the commuting patterns between these two panels.

[1] The hierarchical agglomerative clustering method initially treats each municipality as a separate unit, with the "distance" between municipalities determined by the proportion of commuters relative to workers. Municipalities are merged if their distance is below a specified cutoff level. Furthermore, the distance between groups is calculated as the average of distances between all possible combinations of municipalities within the groups, and groups are merged if their distance is below the cutoff. This process is repeated until all cluster distances exceed the cutoff, resulting in the formation of commuting zones (CZs). Tolbert and Sizer (1996) developed labor market areas with a minimum population of 100,000. In cases where commuting zones fell below this threshold, they combined commuting zones to form labor market areas until the population requirement of 100,000 was met.

[2] Source: http://qianxi.baidu.com/

Next, we use the migration data in 2023 to mitigate the concern of COVID-19 pandemic lockdown. Figure 1 indicates that the national average daily migration during 2023 Spring Festival has returned to the level in 2019. Figure 2 shows the daily migration during Spring Festival from 2019 to 2023. We find that the trend of 2023 presents similarity to that of 2019. As a result, from 369 prefecture-level cities and direct-administered counties, we construct 74 LMAs in China.[3] Panel A of Figure 3 presents a nationwide colored map delineating China's labor market areas. Cities sharing the same color are categorized within the same LMA. Notably, the map highlights Tier 1 cities, such as Beijing, Shanghai, Guangzhou, and Shenzhen. Panel B of Figure 3 shows a close-up of the three largest LMAs, Beijing-Shanghai, Shenzhen, and Guangzhou area. This observation aligns with the prevailing trend wherein workers are attracted to these first-tier mega cities due to the potential job opportunities.[4] Section IA.1 of the Online Appendices describes the delineation results.

3.2 Land reform roll-out

We obtained information on the implementation of land reform at the local county level in China from the Ministry of Agricultural and Rural Affairs. The data spans from the initial launch of land reform in 2009 to 2019 and covers 2,286 counties, which represents more than 80% of China's total counties. The data provides precise records of the start and completion dates of land reform for each county. The start of land reform is determined by the issuance of the first certificate to a household within the county. Once the land reform is initiated in a county, residents are aware that they will have property rights, which motivates them to transition from their own-land-based activities.On average, it took approximately one-and-a-half years to complete the reform in an entire county.

The land reform program initially began as a pilot project in eight villages in 2009, following the issuance of the "No. 1 Document" by the central government. It was then expanded nationwide in

[3]Previous studies construct LMAs from county-to-county flow (Bishop et al., 2021; Daisuke et al., 2020; Tolbert and Sizer, 1996), but we are only able to analyze city-to-city flow due to the data limitation. Thus, the number of LMAs in China is less than that in US, Japan, and Australia.

[4]See for example: https://country.eiu.com/article.aspx?articleid=1326926316&Country=China&topic=Economy and https://www.chinadaily.com.cn/a/202211/30/WS6386e6fca31057c47eba1e7a.html

2011 with the release of the "Opinions on the Pilot of the Rural Land Certification Program" by the Ministry of Agriculture. The program further expanded, covering 15 counties in 2014, 1,729 counties in 2016, and 2,117 counties in 2018. The reform was implemented gradually, with different counties adopting it at different times. In our study, we consider 2012 as the start of the treatment year, as this is when the program was implemented nationwide. We exclude the nine counties that were part of the pilot project in 2009 and 2010. We then match the land reform data with local labor market delineation using the administrative division codes.

3.3 Financial data

We obtain private firm-level variables for leverage and financial controls from the Chinese Industrial Enterprise Database (CIED), also referred to as the Chinese Industry Business Performance Database (CIBPD). This extensively used database (Hau et al., 2020; Hsieh and Klenow, 2009; Liu et al., 2021; Song et al., 2011) covers all establishments from 2008 to 2015 and provides firm-level information such as physical addresses, the administrative division codes of the city of operation, ownership structure, industry (tabulation categories identified by letters - China's Industrial Classification for National Economic Activities (CISIC))[5], and basic financial data. Based on the data availability, our sample of private firms includes 2,102,390 enterprises in 360 cities, resulting in 5,155,124 firm-year observations.[6] We obtain public firm-level variables from CSMAR database for the same sample period. Our sample of publicly traded firms comprises 1,819 enterprises in 241 cities, resulting in 8,313 firm-year observations.[7] We then merge the financial data with LMAs delineation using the administrative division codes.

[5] The current industry classification standard in China is the Industrial Classification for National Economic Activities (CISIC) (http://www.stats.gov.cn/tjsj/tjbz/201709/t20170929_1539288.html), generally adapted from the International Standard Industrial Classification of All Economic Activities (ISIC) issued by the United Nations. (https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf)

[6] Hong Kong SAR, Macao SAR, and Taiwan are excluded from our analysis due to the lack of data.

[7] We exclude financial firms in both samples following previous studies (Kisgen, 2009), since leverage for these firms may have a different implication than those for non-financial firms.

4 Effect of land titling reform on firm leverage

4.1 Baseline results

We aim to estimate how implementation of the land titling reform affects the capital structure of both private and publicly traded firms. To capture this we follow the staggered difference-in-differences (DiD) and estimate the following specification:

$$Leverage_{ijt} = \delta_i + \delta_j + \delta_t + \beta_1 TreatedLMA_{ijt} + \gamma Z_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where $Leverage_{ijt}$ represents the debt-to-capital ratio of firm i located in LMA j in year t. The debt-to-capital ratio is defined as the total debt (long-term plus short-term debt) divided by the sum of book value of equity and total debt. δ_i, δ_j, and δ_t are firm, LMA, and year fixed effects. $TreatedLMA_{ijt}$ is an indicator variable equal to one if the firm operates in the LMAs where the land reform has been implemented by year t, and zero otherwise; this term is set to zero for the firms operate in the LMAs without the reform in any t. Once the land reform is initiated in a county, residents are aware that they will secure clear property rights, which motivates them to transition from their own-land-based activities and migrate within the local labor market. Thus, we use the start date of the land reform to determine $TreatedLMA_{ijt}$. Z_{ijt} is a set of firm-level control variables, including *Log assets*, *ROA*, *Sales growth*, *Capex*, *Cash holdings*, *Labor intensity*, *Zscore*, and *MTB*.[8] Standard errors are clustered at the firm level and all variables are defined in Appendix A. 1. We estimate the specification separately in samples of private and publicly traded firms.[9]

Table 1 presents firm-level characteristics for samples of private (Panel A) and publicly traded (Panel B) firms. On average, private firms have higher leverage, smaller assets, lower sales growth, and higher labor intensity than public firms (column (2)). Approximately half of the publicly traded firms are state-owned enterprises (SOE), while the majority of private firms (at least 75%) are non-SOEs. Around 36.3% and 42.3% of the observations in private and public firms samples,

[8] All continuous variables are winsorized at 1% and 99%.

[9] We include *Zscore private* when estimating the private firm sample and include *Zscore public* and *MTB* when estimating the publicly traded firm sample.

respectively, are treated at some point during the sample period.

Table 2 presents the results of this baseline test. Columns (1) to (3) (columns (4) to (6)) report the results for the sample of private (publicly traded) firms. Columns (1) and (4) only include the firm, LMA, and year fixed effects. Columns (2) and (5) also include the firm-level control variables. To control for time-varying industrywide shocks, the specification in columns (3) and (6) add CISIC industry-by-year fixed effects. Across all the specifications, the coefficient on the $TreatedLMA_{ijt}$ is negative and statistically significant for private firms, while the coefficient is positive and statistically significant for publicly traded firms.

These results suggest that leverage ratios of private firms in treated LMAs decrease relative to the leverage ratios of firms in untreated LMAs. However, the leverage ratios of publicly traded firms in treated LMAs increase compared to those in untreated LMAs. Since the sample size of private firms is significantly larger than that of publicly traded firms, we also create a panel of matched public and private firms and re-estimate the baseline model in Section 6. In the next section, we address the concerns regarding to the parallel trends assumption when using a DiD model.

4.2 Dynamic effects of land titling reform on firm leverage

The results in Table 2 support our hypotheses, yet the validity of the DiD framework depends on the parallel trends assumption. To alleviate the concern, we estimate the dynamic effects of implementation of the land titling reform on the capital structure of private and public firms. By estimating a dynamic regression, we control for pre-existing trends in the dependent variable and check whether the parallel trends assumption holds. We use the following specification:

$$Leverage_{ijt} = \delta_i + \delta_j + \delta_t + \beta_k \sum_{k=-4}^{-2} d[t+k]_{ijt} + \beta_k \sum_{k=0}^{3} d[t+k]_{ijt} + \gamma Z_{ijt} + \varepsilon_{ijt}, \qquad (2)$$

This specification is similar to that in Equation 1, with the exception that the indicator variable $TreatedLMA_{ijt}$ is replaced with the seven indicator variables $d[t+k]_{ijt}$, $-4 \leq k \leq -2$ or $0 \leq k \leq 3$, which are equal to one for the firm that operates in the LMAs in four years before or three years after the land titling reform.[10] Table 3 reports the results. We find that all the coefficients for $d[t+k]_{ijt}$ in the pre-treatment periods ($-4 \leq k \leq -2$) are statistically insignificant for private and public firms. The significant coefficients for private firms occur from the year of implementation of the land titling reform (year "t"). For example, one year after the land reform, the leverage of private firms decreases significantly at the 1% level by 1.368 percentage points on average, compared to one year before the reform. The significant coefficients for publicly traded firms occur two years after the implementation of the reform. Figure 4 depicts the dynamic effects. This suggests that the parallel trends assumption of a DiD model holds and the estimates in Table 2 are valid.

4.3 Mechanisms for the effects

The results in the previous sections align with our hypothesis that publicly traded firms increase their leverage following the implementation of the land titling reform to take advantage of the lower cost of labor and indirect costs of financial distress. Nevertheless, private firms opt to decrease their leverage after the reform to maintain financial flexibility and increase matching probability in the local labor markets. In this section, we explore the mechanisms that drive the effects of LTP on leverage.

First, the land titling reform is expected to create a shock of labor supply in the local labor market. Assuming LTP is effective, we would expect an increase in the number of labor in the local labor markets. To test this hypothesis, we estimate the following specification:

$$Workforce_{ejt} = \delta_e + \delta_j + \delta_t + \beta_1 TreatedLMA_{ijt} + \gamma X_{ijt} + \varepsilon_{ijt}, \tag{3}$$

where $Workforce_{ejt}$ represents the number of laborers in city e located in LMA j in year t. We obtain the number of labor in each city from China Labor Statistics Yearbook during the period from 2008 to 2015.[11] X_{ijt} is a set of city-level control variables, including *GDPpc, Population,* and

[10] $\{\beta_k\}$ are estimated relative to β_{-1}, which is omitted. Thus all event time indicators represent leverage ratio relative to one year before the implementation of the land titling reform.

[11] https://www.chinayearbooks.com/tags/china-labour-statistical-yearbook

Area. Standard errors are clustered at the city level and all variables are defined in Appendix A. 1.

Panel A of Table 4 presents the results of this baseline test. The result in column (1) is consistent with our conjecture that the number of laborers increases in the local labor market following the LTP implementation. Typically, in a local labor market, workers often migrate from their hometowns to working cities, resulting in the presence of both labor import and export cities. Assuming that LTP stimulates an increase in labor supply in the local labor market, it is expected that the number of labor increases more in the labor import cities within the LMAs. To test this, we calculate the net traffic outflow ($outflow - inflow$) for each city before the 2023 Chinese Lunar New Year, utilizing Baidu Qianxi data.[12] $Import$ is defined as equal to one if the net traffic outflow is positive and zero otherwise.[13] Firms in cities with $Import$ equal to one is considered as a labor import city. Column (2) presents the results estimating Equation 3 with subsamples of labor import cities. The results align with our expectation.

If the land titling reform can reduce the cost of labor and financial distress, we would expect a decrease in the wage premium following LTP implementation. The conceptual framework in Section 2.2 suggests that the compensation premium for the risk of job loss is the cost of financial distress. Specifically, workers would require a higher wage for earnings loss risk if the firm has higher leverage. Assuming the reform increases the labor supply, this risk is expected to decrease and the wage may decrease. Further, when private firms decrease their leverage after the reform to attract more worker, we would expect an increase in their number of employees.

To examine this hypothesis, we estimate the following specification:

$$Outcome_{ijt} = \delta_i + \delta_j + \delta_t + \beta_1 TreatedLMA_{ijt} + \gamma Z_{ijt} + \varepsilon_{ijt}, \tag{4}$$

where $Outcome_{ijt}$ includes the average annual pay and the number of employees of firm i located in LMA j in year t. *Employee* is defined as the number of employees for each firm and

[12] 2023 Chinese Lunar New Year is on 23 January 2023.

[13] Workers tend to return to their hometown from working cities prior to the Chinese Lunar New Year. Thus, cities with positive net traffic outflow before the Chinese Lunar New Year are considered labor import cities.

$Wage$ is calculated as total wage divided by the number of total employees ($Employee$).[14,15] All control variables from Table 2 are included and all variables are defined in Appendix A. 1.

Panel A of Table 4 presents the results. Columns (1) and (3) show that wages of private and public firms decrease following the reform. This suggests that workers tend to require smaller compensating differentials for earning loss risk in a larger market, implying a reduced cost of labor and financial distress. In contrast, we only find a statistically significant effect on the number of employees for private firms (column (2)). Column (4) shows that there is no significant change in the number of employees for public firms. This insignificant employee change, combined with significant wage decrease, could imply that publicly traded firms reduce their cost of labor for incumbent employees, thus increasing their leverage after the reform. On the other hand, private firms reduce their leverage to attract new workers in the local labor markets.

5 Cross-sectional Heterogeneity

The implementation of the land titling reform may elicit different reactions from firms in different industries operating in different cities. In this section, we examine how characteristics of city and firm can moderate firms' capital structure decisions. This contributes to the understanding of how the two competing factors discussed in Section 2.2 shape the capital structure decision of private and public firms.

5.1 City-level heterogeneity

Assuming that LTP stimulates an increase in labor supply in the local labor market, it is expected that the land titling reform would have a significant effect on firms operating in the labor import cities within the LMAs. To test this hypothesis, we use the $Import$ described in Section 4.3 to split the full sample. Firms in cities with $Import$ equal to one (zero) enter a labor import (export)cities subsample. We implement the DiD regression in Equation 1 for these subsamples.

[14] $Workforce$ is a city-level measure of workers and $Employee$ is a firm-level measure. $Workforce$ represents the number of total labor in the local labor market but they may not be employed. $Employee$ represents the number of employed labor for firms.

[15] Firms' total wage can be obtained from their financial statements. The sample size of private firms decreases to 3,872,905 and the sample size of publicly traded firms decreases to 4,610 due to data limit.

Table 5 presents the results. Columns (1), (3), (5), and (7) include the firm, LMA, and year fixed effects, while columns (2), (4), (6), and (8) include the firm, LMA, and industry-by-year fixed effects. The results align with our prediction. The decrease in private firms' leverage and the increase in public firms' leverage are only significant in firms operating in the labor import cities. The difference between two coefficients for private firms is significant at the 1% level, while the difference for public firms is significant at the 10% level.

5.2 Firm-level heterogeneity

In this section, our cross-sectional test examines how various firm characteristics, including ownership, size, labor intensity, and firm-level financial constraints, influence private and public firms' capital structure decision. We impletement the DiD regression in Equation 1 for subsamples based on firm characteristics.

5.2.1 Ownership interactions

Existing studies reveal that state-owned firms tend to be more leveraged than non-SOEs (e.g., Dewenter and Malatesta, 2001). Unique to China, the role of government in corporate financing decisions is crucial because it acts as both a majority shareholder in state firms and the owner of all major banks. As a result, SOEs in China enjoy preferential access to financing (Chen et al., 2019; Liu et al., 2018). Assuming that LTP reduces the cost of labor and the indirect costs of financial distress, it is anticipated that SOEs would increase their leverage. However, non-SOEs may face a disadvantage compared to their SOE counterparts in terms of access to financing and attracting talents (Kong and Kong, 2017). Consequently, they may reduce their leverage to maintain financial flexibility and attract workforce in the local labor market.

Panel A of Table 6 presents the results pertaining to firm ownership. We use SOE to split firms into SOE and non-SOE subsamples. SOE is an indicator variable equal to one if the firm is a state-owned enterprise and zero otherwise. The results are consistent with our hypothesis. However, we do not find statistically significant results for non-listed SOEs. This could be attributed to the common occurrence of non-listed SOEs in China having majority-owned listed subsidiaries (Huang and Veron, 2021). If this is the case, it is likely that they tend to finance through their subsidiaries due to the lower borrowing costs. The difference between the coefficients in the subsamples is significant at the 1% level for both private and public firms.

5.2.2 Firm size interactions

Next, we examine how firm size may influence their capital structure decision following the implementation of the land titling reform. Firm size is closely related to financial constraints and positively associated with leverage (Hadlock and Pierce, 2010). This implies that large firm may choose to increase their leverage after the reform, while small firms may opt to reduce their leverage to retain financial flexibility. Panel B of Table 6 presents the results.

We use *Size* to split firms into large and small subsamples. *Size* is calculated as the natural logarithms of inflation-adjusted to 2010 book assets in year *t-1*. Large (small) firms have a *Size* value above (below or equal to) the median for year *t-1*. For public firms, the results support our hypothesis. Conversely, for private firms, the implementation of the reform has a negative effect on leverage for both large and small firms. This could suggest that private firms prioritize maintaining their financial flexibility. Consistent with our hypothesis, small private firms reduce more leverage than large private firms.

5.2.3 Financial constraint interactions

We investigate further the role of financial constraints on moderating firms' capital structure decisions after the reform. Assuming that LTP reduces the cost of labor and the indirect costs of financial distress, it is expected that a financially constrained firm would benefit more than a firm that is not financially constrained. If this is the case, we hypothesize that financially constrained firm would increase more leverage. However, the decrease in workers' bargaining power after the reform may allow financially constrained firms to reduce leverage and retain financial flexibility.

Non-financially constrained firms may not need to take advantage of the reduced cost of labor. Nevertheless, when there is an increased competition for labor, it is expected that they may reduce their leverage to attract workers and increase their matching probability. We use the Size-Age

(SA) index from Hadlock and Pierce (2010) to categorize firms into financially and non-financially constraint subsamples.[16] Firms with a SA index value above (below or equal to) the median for year *t-1* enter a financially (non-financially) constrained subsample.[17]

Panel C of Table 6 presents the results. Financially constrained public firms choose to increase their leverage and take advantage of the lower cost of labor, while financially constrained private firms prioritize retaining financial flexibility by decreasing their leverage. For non-financially constrained firms, we only find significant results in private firms. This implies that non-financially constrained listed firms may posses the ability to attract workers through favorable working conditions, especially when compared to their private counterparts (Lyria et al., 2017). If this is the case, they may not need to decrease leverage or their cost of hiring probability.

5.2.4 Labor intensity interactions

Our final firm-level cross-sectional test examines how firms' investment focus may influence their response to the implementation of LTP. The land titling reform generates a shock to labor-intensive firms that rely heavily on labor in comparison to capital-intensive firms. It is expected that labor-intensive firms would benefit more significantly from the reduced cost of labor and the expanded larger labor market resulting from the reform. Consequently, labor-intensive firms should respond more sensitively following LTP as compared to capital-intensive firms. Assuming that LTP reduces the cost of labor and the indirect costs of financial distress, it is expected that labor-intensive firms would opt to increase their leverage. However, due to the increase in labor supply and heightened competition for workers, these firms may choose to reduce their leverage to attract a larger pool of potential employees, considering that their production processes rely heavily on workforce,

Panel D of Table 6 presents the results. Labor intensity is measured by the number of total employees in year *t-1* divided by real assets in million CNY in constant 2010 dollars year *t-1*. Firms with labor intensity values above the median for year *t-1* are classified as labor-intensive,

[16] The calculation of traditional financial constraint index, Whited-Wu Index (Whited and Wu, 2006) and Kaplan-Zingales Index (Kaplan and Zingales, 1997), is not applicable to private firms as it requires dividend payment. The calculation of SA index is defined in Appendix A.1

[17] The sample size of private firms reduces to 3,882,529 due to data limit.

while others are considered capital-intensive. The results align with our prediction that the effect of LTP implementation is only statistically significant for labor-intensive firms. Interestingly, both labor-intensive private and public firms choose to decrease their leverage and attract a larger workforce.

Overall, the results presented in this section emphasize the diverse responses of different firms to a labor supply shock to local labor markets. The findings also shed light on the various mechanisms that private and public firms may employ when making their capital structure decisions.

6 Additional Tests

6.1 Matched sample of private and public firms

Given that the sample size of private firms is significantly larger than that of publicly traded firms, we create a panel of matched public and private firms and re-estimate the DiD regression. To construct the matched sample, we match private firms to publicly traded firms on *Age*, *Log sales*, and *Cash holdings* in year 2011 (before the reform), using propensity score matching. Following (Phillips and Sertsios, 2014), we estimate the following specification using the matched sample:

$$Leverage_{ijt} = \delta_i + \delta_j + \delta_t + \beta_1 TreatedLMA_{ijt} + \beta_2 TreatedLMA_{ijt} \times Private_{ijt} + \gamma Z_{ijt} + \varepsilon_{ijt}, \quad (5)$$

where $Private_{ijt}$ is an indicator variable equal to one for the firm is private. Consistent with our baseline results, we expect β_2 to be negative. If β_2 is negative, private firms raise less debt than publicly traded firms following LTP implement. Column (1) of Table 7 presents the results. The coefficient for $TreatedLMA_{ijt} \times Private_{ijt}$ is significantly negative at the 5% level, supporting our hypothesis.

6.2 Alternative TWFE estimators

The concern regarding the utilization of a standard two-way fixed effects (TWFE) estimator is that it is vulnerable to potential bias in the estimation when treatments are heterogeneous across groups and time periods (Baker et al., 2022). To address the potential issues associated with the standard TWFE estimator, we use three alternative TWFE estimators that are widely used in the literature. The first estimator (SA) is developed by Sun and Abraham (2021) and the second estimator (CS) is developed by Callaway and Sant'Anna (2021). The third approach is the stacked DiD developed by Cengiz et al. (2019) and Wang et al. (2019). We re-estimate the regression from Equation 1.

Columns (2) to (7) of Table 7 presents the results. Across specification for private firms, the impletement of the land titling reform has a significantly negative impact on the leverage ratio. Across specification for publicly traded firms, except for CS estimator, we find a significantly positive effect of the land titling reform on firm leverage. Overall, our baseline results from staggered DiD specification provide valid estimates of the causal interpretation.

7 Conclusion

This paper examine how increased labor supply in the local labor market where firms operate affect their capital structure decisions. To test this, we exploit the staggered introduction of China's land titling program as a sudden increase in labor supply to examine how private and publicly traded firms change their leverage ratios in response to the reform. We begin by construction 74 local market areas using Baidu Qianxi (Baidu Mobility) migration data from 1 January 2023 to 12 February 2023 and a hierarchical agglomerative clustering method developed by Tolbert and Sizer (1996) and Tolbert and Killian (1987). We first implement a staggered DiD regression framework to analyze firms' capital structure decisions. Additionally, we conduct dynamic regression to show that the parallel trends assumption holds in our analyses.

Overall, we find that private firms reduce their leverage following the LTP implement, while publicly traded firms increase their leverage. Additional analyses show that wages of private and public firms decrease after the reform and the number of employees for private firms increases. This suggests that publicly traded firms take advantage of the reduced cost of labor for incumbent employees and increase their leverage after the reform. On the other hand, private firms prioritize financial flexibility and reduce their leverage, despite the lower cost of labor. Furthermore, we exploit several dimensions of cross-sectional heterogeneity, including labor import/export cities, firm ownership, firm size, financially constraint, and investment focus. Overall, our results suggest that the increased labor supply in the local labor market where firms operate is a crucial determinant of capital structure decisions and private and publicly traded firms respond differently to changes in local labor markets.

References

Acemoglu, D., S. Johnson, and J. A. Robinson (2001). The colonial origins of comparative development: An empirical investigation. *American economic review 91*(5), 1369–1401.

Agrawal, A. K. and D. A. Matsa (2013). Labor unemployment risk and corporate financing decisions. *Journal of Financial Economics 108*(2), 449–470.

Al-Sabah, T. and P. Ouimet (2021). For better or worse? the economic implications of paid sick leave mandates. *The Economic Implications of Paid Sick Leave Mandates (October 30, 2021).*

Altman, E. I., M. Iwanicz-Drozdowska, E. K. Laitinen, and A. Suvas (2017). Financial distress prediction in an international context: A review and empirical analysis of altman's z-score model. *Journal of International Financial Management & Accounting 28*(2), 131–171.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics 144*(2), 370–395.

Berk, J. B., R. Stanton, and J. Zechner (2010). Human capital, bankruptcy, and capital structure. *The Journal of Finance 65*(3), 891–926.

Bishop, J., E. Greenland, et al. (2021). *Is the Phillips Curve Still a Curve?: Evidence from the Regions.* Reserve Bank of Australia.

Brav, O. (2009). Access to capital, capital structure, and the funding of the firm. *The journal of finance 64*(1), 263–308.

Bronars, S. G. and D. R. Deere (1991). The threat of unionization, the use of debt, and the preservation of shareholder wealth. *The Quarterly Journal of Economics 106*(1), 231–254.

Brown, J. and D. A. Matsa (2016). Boarding a sinking ship? an investigation of job applications to distressed firms. *The Journal of Finance 71*(2), 507–550.

Bu, D. and Y. Liao (2022). Land property rights and rural enterprise growth: Evidence from land titling reform in china. *Journal of Development Economics 157*, 102853.

Byoun, S. (2011). Financial flexibility and capital structure decision. *Available at SSRN 1108850*.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics 134*(3), 1405–1454.

Chen, H., R. Li, and P. Tillmann (2019). Pushing on a string: State-owned enterprises and monetary policy transmission in china. *China Economic Review 54*, 26–40.

Clark, B. J. (2010). The impact of financial flexibility on capital structure decisions: Some empirical evidence. *Available at SSRN 1499497*.

Daisuke, A., F. Taiyo, K. Daiji, S. Yukiko, et al. (2020). Commuting zones in japan. Technical report.

De Janvry, A., K. Emerick, M. Gonzalez-Navarro, and E. Sadoulet (2015). Delinking land rights from land use: Certification and migration in mexico. *American Economic Review 105*(10), 3125–3149.

DeAngelo, H. and L. DeAngelo (2007). Capital structure, payout policy, and financial flexibility. *Marshall School of Business Working Paper NO. FBE 02-06*.

Deininger, K., D. A. Ali, and T. Alemu (2011). Impacts of land certification on tenure security, investment, and land market participation: evidence from ethiopia. *Land Economics 87*(2), 312–334.

Deininger, K. and S. Jin (2009). Securing property rights in transition: Lessons from implementation of china's rural land contracting law. *Journal of Economic Behavior & Organization 70*(1-2), 22–38.

Denis, D. J. and S. B. McKeon (2012). Debt financing and financial flexibility evidence from proactive leverage increases. *The Review of Financial Studies 25*(6), 1897–1929.

Dewenter, K. L. and P. H. Malatesta (2001). State-owned and privately owned firms: An empirical analysis of profitability, leverage, and labor intensity. *American Economic Review 91*(1), 320–334.

Ding, C. (2003). Land policy reform in china: assessment and prospects. *Land use policy 20*(2), 109–120.

Field, E. (2007). Entitled to work: Urban property rights and labor supply in peru. *The Quarterly Journal of Economics 122*(4), 1561–1602.

Fisman, R., H. Lin, C. Sun, Y. Wang, and D. Zhao (2021). What motivates non-democratic leadership: Evidence from covid-19 reopenings in china. *Journal of Public Economics 196*, 104389.

Graham, J. R. (2022). Presidential address: Corporate finance and reality. *The Journal of Finance 77*(4), 1975–2049.

Hadlock, C. J. and J. R. Pierce (2010). New evidence on measuring financial constraints: Moving beyond the kz index. *The review of financial studies 23*(5), 1909–1940.

Hau, H., Y. Huang, and G. Wang (2020). Firm response to competitive shocks: Evidence from china's minimum wage policy. *The Review of Economic Studies 87*(6), 2639–2671.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Hu, X., Z. Chen, X. Chen, and Z. Liu (2023). The political trust impacts of land titling in china. *Land Use Policy 129*, 106656.

Huang, T. and N. Veron (2021). China's top-ranked corporations are not as opaque as they may seem.

Jia, J. S., X. Lu, Y. Yuan, G. Xu, J. Jia, and N. A. Christakis (2020). Population flow drives spatio-temporal distribution of covid-19 in china. *Nature 582*(7812), 389–394.

Kaplan, S. N. and L. Zingales (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The quarterly journal of economics 112*(1), 169–215.

Kim, H. (2020). How does labor market size affect firm capital structure? evidence from large plant openings. *Journal of Financial Economics 138*(1), 277–294.

Kisgen, D. J. (2009). Do firms target credit ratings or leverage levels? *Journal of financial and quantitative analysis 44*(6), 1323–1344.

Kong, G. and D. Kong (2017). Corporate governance, human capital, and productivity: evidence from chinese non-listed firms. *Applied Economics 49*(27), 2655–2668.

Liu, L., R. Wang, W. W. Guan, S. Bao, H. Yu, X. Fu, and H. Liu (2022). Assessing reliability of chinese geotagged social media data for spatiotemporal representation of human mobility. *ISPRS International Journal of Geo-Information 11*(2), 145.

Liu, P. (2019). A model of capital structure under labor market search. *Available at SSRN 3038469*.

Liu, Q., X. Pan, and G. G. Tian (2018). To what extent did the economic stimulus package influence bank lending and corporate investment decisions? evidence from china. *Journal of Banking & Finance 86*, 177–193.

Liu, Z., H. Shen, M. Welker, N. Zhang, and Y. Zhao (2021). Gone with the wind: An externality of earnings pressure. *Journal of Accounting and Economics 72*(1), 101403.

Luo, B. (2018). 40-year reform of farmland institution in china: Target, effort and the future. *China Agricultural Economic Review*.

Lyria, R. K., G. Namusonge, and K. Karanja (2017). The effect of talent attraction on organizational performance of firms listed in the nairobi securities exchange. *Journal of Human Resource and Leadership 1*(3), 18–30.

Matsa, D. A. (2010). Capital structure as a strategic variable: Evidence from collective bargaining. *The Journal of Finance 65*(3), 1197–1232.

Matsa, D. A. (2018). Capital structure and a firm's workforce. *Annual Review of Financial Economics 10*, 387–412.

Petrongolo, B. and C. Pissarides (2006). Scale effects in markets with search. *The Economic Journal 116*(508), 21–44.

Phillips, G. and G. Sertsios (2014). Financing decisions and product introductions of private and publicly traded firms. Technical report, National Bureau of Economic Research.

Sanati, A. (2022). How does labor mobility affect corporate leverage and investment? *Available at SSRN 2986582*.

Saunders, A. and S. Steffen (2011). The costs of being private: Evidence from the loan market. *The Review of Financial Studies 24*(12), 4091–4122.

Schwarzwalder, B., R. Prosterman, Y. Jianping, and J. Riedinger (2002). An update on china's rural land tenure reforms: Analysis and recommendations based on a seventeen-province survey. *Colum. J. Asian L. 16*, 141.

Serfling, M. (2016). Firing costs and capital structure decisions. *The Journal of Finance 71*(5), 2239–2286.

Song, Z., K. Storesletten, and F. Zilibotti (2011). Growing like china. *American economic review 101*(1), 196–233.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199.

Titman, S. (1984). The effect of capital structure on a firm's liquidation decision. *Journal of financial economics 13*(1), 137–151.

Tolbert, C. M. and M. Killian (1987). *Labor Market Areas for the United States. Washington, DC: Department of Agriculture.* Economic Research Service, Agricultural and Rural Economics Division.

Tolbert, C. M. and M. Sizer (1996). Us commuting zones and labor market areas: A 1990 update. Technical report.

Vendryes, T. (2010). Land rights in rural china since 1978. reforms, successes, and shortcomings. *China Perspectives 2010*(2010/4).

Wang, J., S. Pant, and T. Yao (2019). Do firms get high? the impact of marijuana legalization on firm performance, corporate innovation, and entrepreneurial activity. *The Impact of Marijuana Legalization on Firm Performance, Corporate Innovation, and Entrepreneurial Activity (June 25, 2019).*

Weiwen, H. (2008). Urbanisation in contemporary china observed: Dramatic changes and disruptions. *Architectural Design 78*(5), 26–31.

Whited, T. M. and G. Wu (2006). Financial constraints risk. *The review of financial studies 19*(2), 531–559.

Yang, M. and Z. Xie (2020). Impacts of fighting covid-19 on china's population flows: An empirical study based on baidu migration big data. *Population Research 44*(4), 74.

Figures and Tables

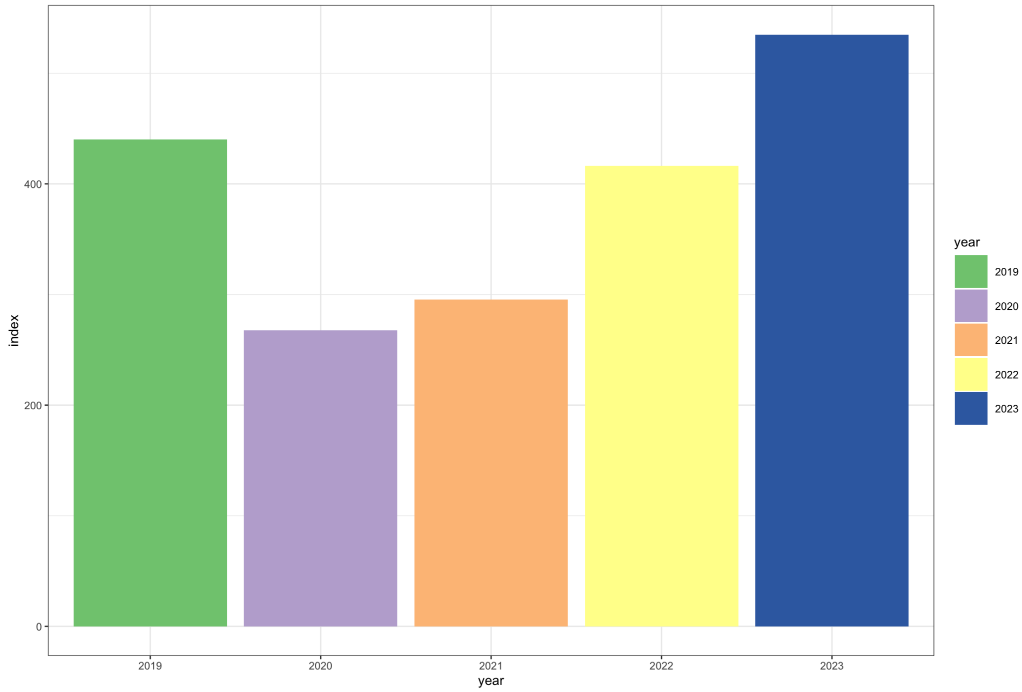


Figure 1. National Average Daily Migration during Spring Festival

This figure shows the natural disaster exposure measured as the total number of incidents between 2014 and 2019 in each city. The darker shade represents more incidents. The unshaded area has no available data.

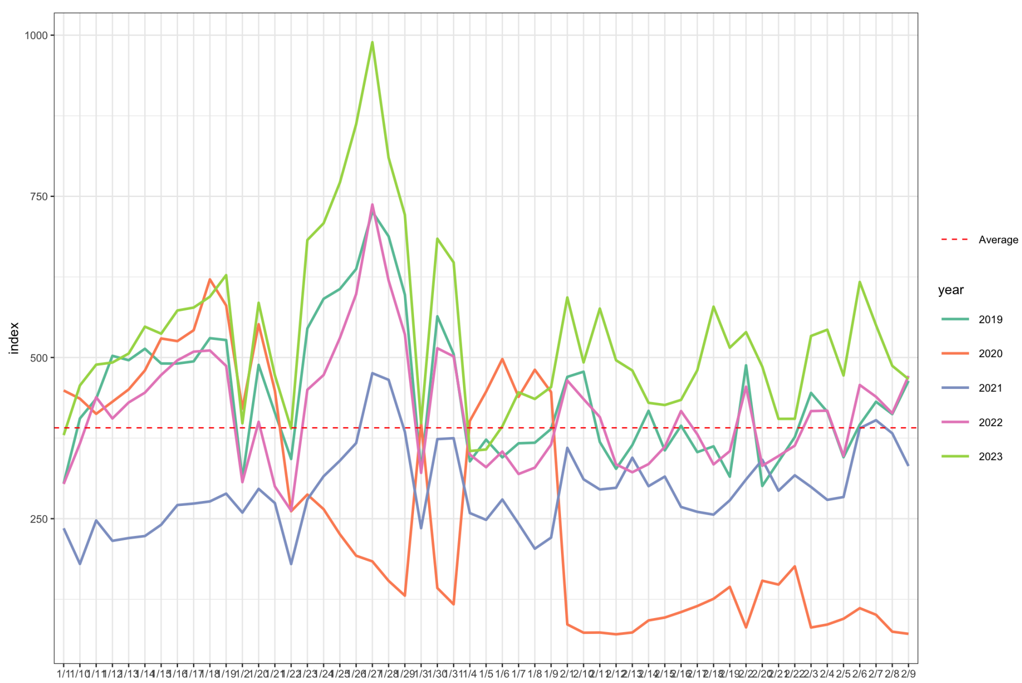
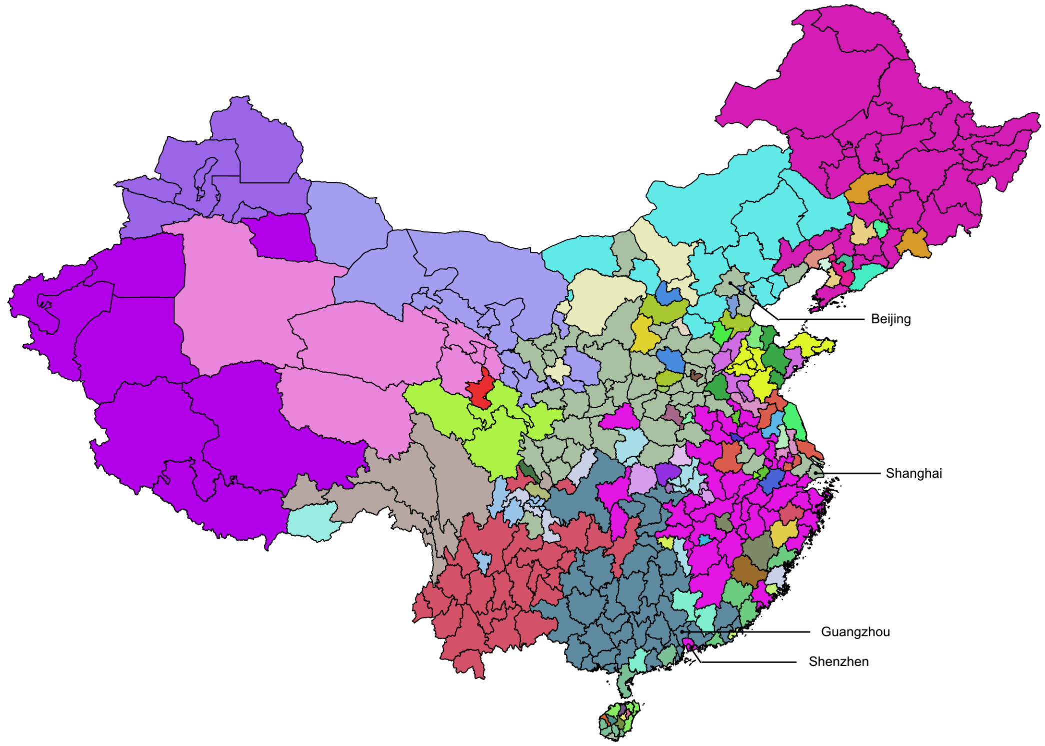
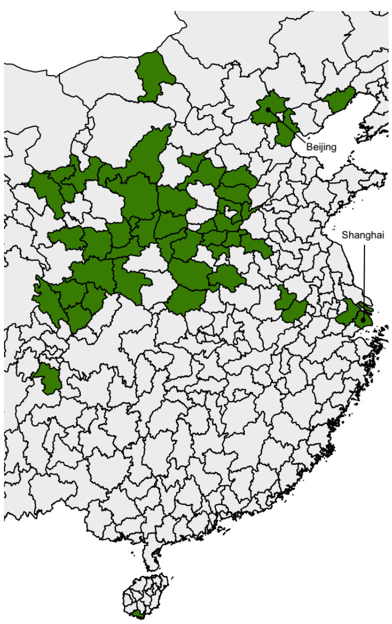


Figure 2. Daily Migration during Spring Festival

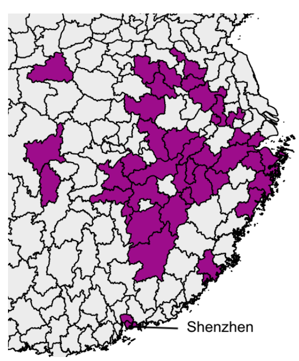
This figure shows the heat map of fintech loan density measured as the total number of successful fintech loan applications between 2010 and 2019 in each city. The darker shade represents more fintech loans. The unshaded area has no available data.



Panel A: Nationwide



(a) Beijing-Shanghai area



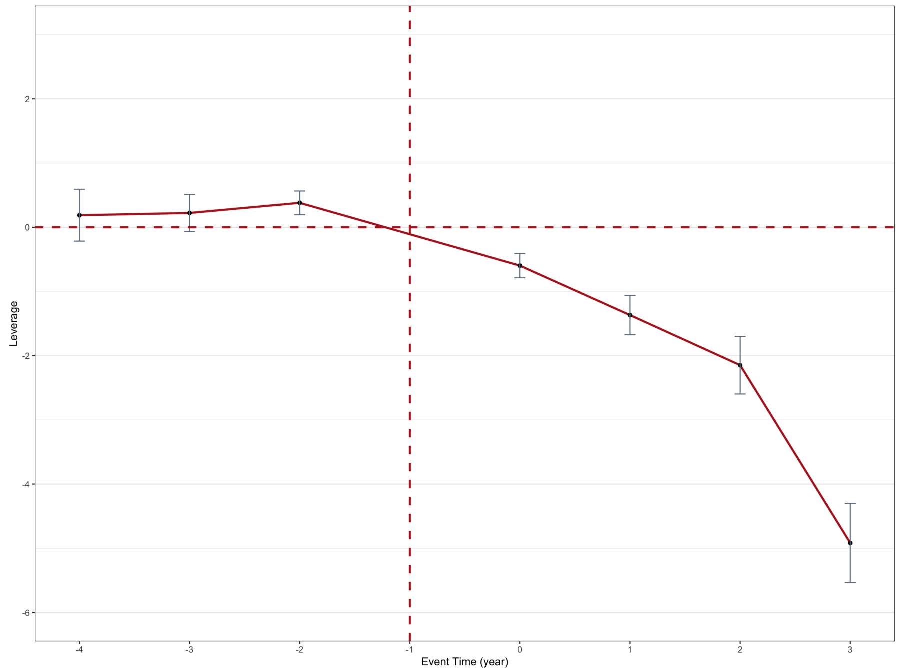
(b) Shenzhen area

(c) Guangzhou area

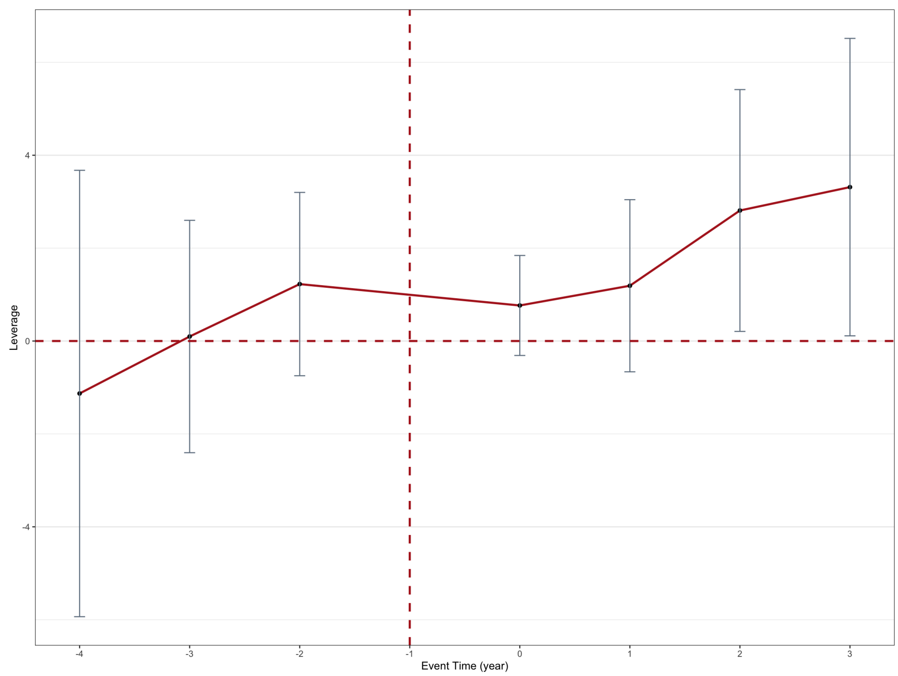
Panel B: Three largest LMAs

Figure 3. LMA Delineation

The colored map is based on the 2023 Baidu Qianxi data and hierarchical agglomerative clustering with average linkage. Cities with the same color belong to the same group. Tier 1 cities include Beijing, Shanghai, Guangzhou, and Shenzhen are indicated in the map, which belong to the top 3 largest labor market areas.



Panel A: Private Firms



Panel B: Publicly Traded Firms

Figure 4. Dynamic Effects of Land Titling Reform

This figure shows the dynamic effects of land titling reform on the leverage of private and publicly traded forms. Panel A presents the results for private firms and Panel B presents the results for public firms. The bands around the coefficient estimates show 95% confidence intervals. The coefficient for "year t-1" is omitted by design in the estimation.

Table 1
Summary Statistics
This table reports the descriptive statistics for firm-year observations from 2008 to 2015. Column (1) indicates the number of observations, columns (2) and (3) show the means and standard deviations, and columns (4) to (6) provide the 25% percentile, median, and 75% percentile. All continuous variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese Yuan (CNY). All variables are defined in Appendix A.1.

Panel A: Private firms

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	N	Mean	SD	25%	Median	75%
Leverage	5,155,124	51.360	49.820	9.430	46.510	79.520
Log assets	5,155,124	2.513	2.291	0.903	2.430	4.058
Tangibility	5,155,124	0.172	0.218	0.008	2.516	3.989
Capex	5,155,124	0.117	0.258	0.000	0.011	0.106
Cash holdings	5,155,124	0.173	0.226	0.021	0.080	0.229
Log sales	5,155,124	2.399	2.387	0.944	2.516	3.989
Sales growth	5,155,124	-0.014	0.864	-0.035	0.000	0.104
ROA (%)	5,155,124	4.300	31.640	-1.190	1.750	7.830
Zscore private	5,155,124	3.537	8.490	0.669	1.607	3.262
Labor intensity (%)	5,155,124	7.180	22.500	0.003	1.340	4.853
ΔLabor	5,155,124	0.499	12.591	0.000	0.000	0.000
SOE	5,155,124	0.052	0.221	0.000	0.000	0.000
TreatedLMA	5,155,124	0.363	0.481	0.0000	0.0000	1.000

Panel B: Publicly traded firms

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	N	Mean	SD	25%	Median	75%
Leverage	8,313	35.600	19.500	20.400	20.400	49.100
Log assets	8,313	15.560	1.280	14.600	15.400	16.300
Tangibility	8,313	0.271	0.187	0.121	0.242	0.397
Capex	8,313	0.080	0.086	0.022	0.053	0.105
Cash holdings	8,313	0.141	0.090	0.077	0.123	0.184
Log sales	8,313	14.860	1.450	13.900	14.700	15.700
Sales growth	8,313	0.136	0.473	-0.017	0.078	0.242
ROA (%)	8,313	4.160	7.360	0.714	3.296	7.059
Zscore public	8,313	2.710	2.820	1.010	1.960	3.510
MTB	8,313	3.220	2.600	1.580	2.460	3.910
Labor intensity (%)	8,313	0.841	0.742	0.308	0.648	1.139
ΔLabor	8,313	0.046	0.204	-0.018	0.009	0.075
SOE	5,155,124	0.560	0.496	0.0000	1.000	1.000
TreatedLMA	8,313	0.423	0.494	0.0000	0.0000	1.000

Table 2
Effect of Land Titling Reform on Leverage

This table presents the effect of land titling reform on the leverage of private and publicly traded firms from 2008 to 2015. Columns (1) to (3) present estimates for private firms using a sample of 5,155,124 firm-years. Columns (4) to (6) present estimates for publicly traded firms using a sample of 8,313 firm-years. The dependent variable in each regression is *Leverage (%)*, defined as total debt (long-term plus short-term debt) divided by the sum of total debt and book value of equity in percentage. *TreatedLMA* is an indicator variable equal to one if the firm i operates in the LMAs where the land reform has been implemented in year t, and zero otherwise; this term is set to zero for firms operate in the LMAs without the reform in any t. Other control variables are defined in Appendix A.1. All continuous variables are winsorized at 1% and 99%. Robust t-statistics clustered at the firm level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:		Private firms			Publicly traded firms	
Dependent variable:		Leverage (%)			Leverage (%)	
TreatedLMA	-0.560***	-0.560***	-0.543***	0.384***	0.368***	0.285*
	(0.082)	(0.082)	(0.082)	(0.081)	(0.094)	(0.239)
Log assets		2.588***	2.583***		7.368***	7.155***
		(0.061)	(0.061)		(2.306)	(2.259)
ROA (%)		-0.053***	-0.053***		-0.666***	-0.624***
		(0.002)	(0.002)		(0.143)	(0.098)
Sales growth		0.940***	0.952***		1.771	1.575
		(0.027)	(0.027)		(2.424)	(2.569)
Capex		-3.274***	-2.786***		12.771***	10.136***
		(0.123)	(0.128)		(4.077)	(1.613)
Cash holdings		0.898***	0.905***		-29.789***	-29.246***
		(0.197)	(0.197)		(5.228)	(3.438)
Labor intensity (%)		0.061***	0.061***		-0.115	-0.104
		(0.003)	(0.003)		(0.639)	(0.554)
Zscore private		-0.289***	-0.290***			
		(0.006)	(0.006)			
Zscore public					-1.324	-1.251
					(1.131)	(0.899)
MTB					1.143	1.245**
					(0.701)	(0.547)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes		Yes	Yes	
Industry ×year FEs			Yes			Yes
Observations	5,155,124	5,155,124	5,155,124	8,313	8,313	8,313
R^2	0.725	0.727	0.728	0.592	0.602	0.611

Table 3
Dynamic Effects of Land Titling Reform
This table presents the dynamic effects of land titling reform on the leverage of private and publicly traded firms. Column (1) reports the results for private firms and column (2) reports the results for publicly traded firms. The dependent variable in each regression is *Leverage (%)*, defined as total debt (long-term plus short-term debt) divided by the sum of total debt and book value of equity in percentage. *d[t+k]*, -4≤k≤3, are seven indicators equal to one for the firm that operates in the LMAs in four years before or three years after the land titling reform. *d[t+k]* is set to zero for the control cities. *d[t-1]* is zero by construction. All control variables from Table 2 are included and are defined in Appendix A.1. Each regression includes firm, LMA, and year fixed effects. All continuous variables are winsorized at 1% and 99%. Robust t-statistics clustered at the firm level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

	(1)	(2)
Sample:	Private firms	Publicly traded firms
Dependent variable:	Leverage (%)	
d[t-4]	0.187	-1.130
	(0.206)	(2.451)
d[t-3]	0.223	0.097
	(0.148)	(1.276)
d[t-2]	0.380	1.226
	(0.194)	(1.007)
d[t-1]	0.000	0.000
	-	-
d[t]	-0.598***	0.765
	(0.096)	(0.549)
d[t+1]	-1.368***	1.190
	(0.155)	(0.945)
d[t+2]	-2.148***	2.810**
	(0.229)	(1.328)
d[t+3]	-4.918***	3.314**
	(0.315)	(1.634)
Controls	Yes	Yes
Firm FEs	Yes	Yes
LMA FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	5,155,124	8,313
R^2	0.727	0.602

Table 4
Labor Market Size and Wages

This table presents the effect of land titling reform on wages and workforce for private and publicly traded firms from 2008 to 2015. Panel A presents the results on local workforce. Panel B presents the results on wages and employees. $Workforce$ is defined as the number of labor in each city. *Employee* is computed as the number of employees for each firm. $Wage$ is calculated as total wage divided by the number of total employees. *TreatedLMA* is an indicator variable equal to one if the firm i operates in the LMAs where the land reform has been implemented in year t, and zero otherwise; this term is set to zero for firms operate in the LMAs without the reform in any t. Panel A includes city-level control variables. Each regression includes the city, LMA, and year fixed effects. Robust t-statistics clustered at the city level are shown in parentheses. All control variables from Table 2 are included in Panel B. Each regression includes the firm, LMA, and year fixed effects. Robust t-statistics clustered at the firm level are shown in parentheses. All variables are defined in Appendix A.1. All continuous variables are winsorized at 1% and 99%. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: Labor market size

	(1)	(2)
Sample:	Full	Labor import
Dependent variable:	Workforce	
TreatedLMA	0.074***	0.113***
	(0.018)	(0.031)
GDPpc	0.163***	0.166***
	(0.050)	(0.053)
Population	1.488**	1.751*
	(0.667)	(0.899)
Area	-0.510	-0.711
	(0.515)	(0.694)
City FEs	Yes	Yes
LMA FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	2,272	1,245
R^2	0.894	0.931

Panel B: Wage and employees

	(1)	(2)	(3)	(4)
Sample:	Private firms		Publicly traded firms	
Dependent variable:	Wage	Employee	Wage	Employee
TreatedLMA	-1.152***	0.608**	-4.493***	-1.507
	(0.065)	(0.286)	(1.659)	(2.384)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	3,872,905	3,872,905	4,610	4,610
R^2	0.714	0.935	0.699	0.954

Table 5
City-level Cross-sectional Heterogeneity

This table presents the effect of land titling reform on the leverage of private and publicly traded firms conditional on labor import and export cities. The dependent variable in each regression is *Leverage (%)*, defined as total debt (long-term plus short-term debt) divided by the sum of total debt and book value of equity in percentage. The determination of labor import and export cities is based on the Baidu Qianxi net traffic outflow form each city before the 2023 Chinese Lunar New Year. *Import* is defined as equal to one if the net traffic outflow is positive and zero otherwise. Firms in cities with *Import* equal to one (zero) enter a labor import (export) cities subsample. *TreatedLMA* is an indicator variable equal to one if the firm i operates in the LMAs where the land reform has been implemented in year t, and zero otherwise; this term is set to zero for firms operate in the LMAs without the reform in any t. All control variables from Table 2 are included and are defined in Appendix A.1. Columns (1) through (2) report the results for private firms and columns (3) through (4) report the results for publicly traded firms. Each regression includes the firm, LMA, and year fixed effects. Robust t-statistics clustered at the firm level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

	(1)	(2)	(3)	(4)
Sample:	Private firms		Publicly traded firms	
Subsample	Labor import	Labor export	Labor import	Labor export
TreatedLMA	-0.607***	0.177	0.747***	0.101
	(0.096)	(0.166)	(0.107)	(2.137)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	3,732,850	1,422,274	6,376	1,606
R^2	0.73615	0.70514	0.593	0.749
TreatedLMA×(import−export)	-0.784***		0.646*	
t-statistic	-4.092		1.902	

Table 6
Firm-level Cross-sectional Heterogeneity

This table presents the effect of land titling reform on the leverage of private and publicly traded firms conditional on firm-level characteristics. Panel A presents the results for interactions based on firm ownership. *SOE* is an indicator variable equal to one if the firm is a state-owned enterprise and zero otherwise. Panel B presents the results for interactions based on firm size. *Size* is calculated as the natural logarithms of inflation-adjusted to 2010 book assets in year *t-1*. Large (small) firms have a *Size* value above (below or equal to) the median for year *t-1*. Panel C presents the results for interactions based on whether the firm is financially constrained. The determination of financially constrained firms versus non-financially constrained firms is based on the Size-Age Index from Hadlock and Pierce (2010). Firms with a SA index value above (below or equal to) the median for year *t-1* enter a financially (non-financially) constrained subsample. Panel D presents the results for interactions based on whether the firms' investment focus. *Labor intensity* is measured by the number of total employees in year *t-1* divided by real assets in million CNY in constant 2010 dollars year t-1. Firms with labor intensity values above the median for year *t-1* are classified as labor-intensive, while others are considered capital-intensive. The dependent variable in each regression is *Leverage (%)*, defined as total debt (long-term plus short-term debt) divided by the sum of total debt and book value of equity in percentage. *TreatedLMA* is an indicator variable equal to one if the firm i operates in the LMAs where the land reform has been implemented in year t, and zero otherwise; this term is set to zero for firms operate in the LMAs without the reform in any t. All control variables from Table 2 are included in Panels A and C. Control variables, *Log assets* and *Labor intensity (%)*, are excluded from panels B and C. All variables are defined in Appendix A.1. Columns (1) and (2) of each panel report the results for private firms and columns (3) and (4) report the results for publicly traded firms. Each regression includes the firm, LMA, and year fixed effects. Robust t-statistics clustered at the firm level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: Ownership Interactions

	(1)	(2)	(3)	(4)
Sample:	Private firms		Publicly traded firms	
Subsample	SOE	non-SOE	SOE	non-SOE
TreatedLMA	0.511	-0.617***	1.162**	-0.750***
	(0.388)	(0.084)	(0.479)	(0.264)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	266,212	4,888,912	4,656	3,657
R^2	0.757	0.730	0.666	0.586
TreatedLMA×(SOE−non-SOE)	1.127***		1.912***	
t-statistic	2.839		3.496	

Table 6
Continued

Panel B: Size Interactions				
	(1)	(2)	(3)	(4)
Sample:	Private firms		Publicly traded firms	
Subsample	Large	Small	Large	Small
TreatedLMA	-0.507***	-0.849***	1.053*	-1.232*
	(0.100)	(0.155)	(0.612)	(0.674)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	2,577,596	2,577,52	4,160	4,153
R^2	0.790	0.776	0.874	0.829
TreatedLMA×(large−small)	0.342*		2.291***	
t-statistic	1.860		2.502	

Panel C: Financial Constraint Interactions				
	(1)	(2)	(3)	(4)
Sample:	Private firms		Publicly traded firms	
Subsample	FC	non-FC	FC	non-FC
TreatedLMA	-0.602***	-0.989***	1.402**	-0.764
	(0.125)	(0.133)	(0.619)	(0.896)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	1,941,267	1,941,262	4,160	4,153
R^2	0.737	0.729	0.853	0.591
TreatedLMA×(FC−non-FC)	0.366**		2.248**	
t-statistic	2.023		2.412	

Table 6
Continued

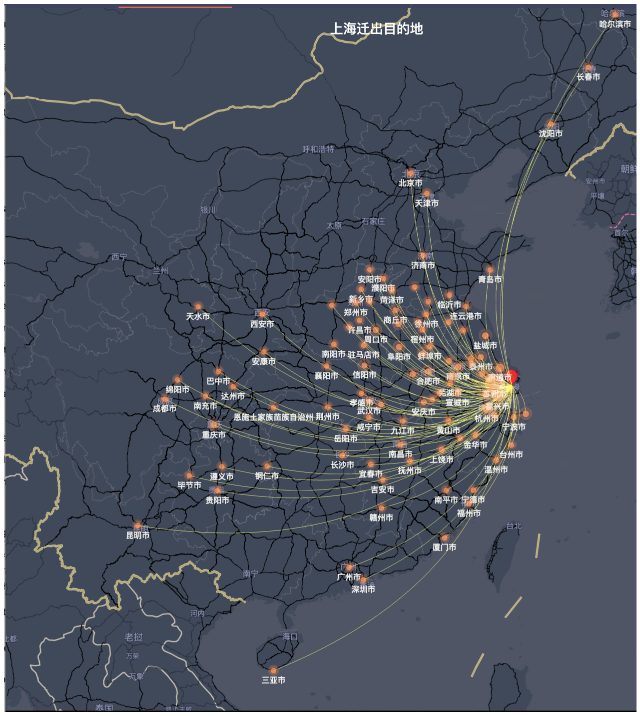
Panel D: Labor Intensity Interactions				
	(1)	(2)	(3)	(4)
Sample:	Private firms		Publicly traded firms	
Subsample	Labor-intensive	Capital-intensive	Labor-intensive	Capital-intensive
TreatedLMA	-0.782***	-0.134	-0.425***	0.131
	(0.136)	(0.099)	(0.162)	(0.863)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	3,218,371	1,936,753	4,160	4,153
R^2	0.766	0.802	0.581	0.837
TreatedLMA×(labor−capital)	-0.648***		-0.556*	
t-statistic	-3.846		-1.633	

Table 7
Validity Test

This table presents the results of various validity tests. Column (1) reports the results using a matched sample of private and publicly traded firms. Columns (2) and (3) report the results using the TWFE estimator developed by Sun and Abraham (2021). Columns (4) and (5) report the results using the TWFE estimator developed by Callaway and Sant'Anna (2021). Columns (6) and (7) report the results using stacked DiD developed by Cengiz et al. (2019) and Wang et al. (2019). The dependent variable in each regression is *Leverage (%)*, defined as total debt (long-term plus short-term debt) divided by the sum of total debt and book value of equity in percentage. *TreatedLMA* is an indicator variable equal to one if the firm i operates in the LMAs where the land reform has been implemented in year t, and zero otherwise; this term is set to zero for firms operate in the LMAs without the reform in any t. All control variables from Table 2 are included and are defined in Appendix A.1. Regressions in columns (1) through (5) include the firm, LMA, and year fixed effects. Regressions in columns (6) through (7) include the cohort-firm, cohort-LMA, and cohort-year fixed effects. Robust t-statistics clustered at the firm level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).Each regression includes the firm, LMA, and year fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Test	DiD	SA		CS		Stacked DiD	
Sample	Matched sample	Private firms	Publicly traded firms	Private firms	Publicly traded firms	Private firms	Publicly traded firms
TreatedLMA	1.620**	-0.541**	1.278	-0.576**	5.072**	-0.749***	0.648**
	(0.675)	(0.244)	(0.657)	(0.061)	(2.340)	(0.052)	(0.295)
TreatedLMA×private	-3.450**						
	(1.607)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LMA FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,332	5,155,124	8,313	-	-	12,947,138	20,045
R^2	0.702	0.727	0.836	-	-	0.649	0.597

Appendix Figures and Tables



Panel A: Traffic Outflow from Shanghai on the first date of 2023 Spring Festival

Panel B: Traffic Inflow to Shanghai on the last date of 2023 Spring Festival

Figure A.1. Baidu Qianxi Data

This figure presents an example of Baidu Qianxi data. Panel A depicts the traffic outflow from Shanghai on the first date of the 2023 Spring Festival. Panel B depicts the traffic inflow to Shanghai on the last date of the 2023 Spring Festival.

Table A.1
Variable definitions

Variable	Definitions
TreatedLMA	An indicator variable equal to one if the firm operates in the labor market areas where the land reform has been implemented by year t, and zero otherwise; this term is set to zero for the firms operate in the labor market areas without the reform in any t.
Leverage	Total debt (long-term plus short-term debt) divided by the sum of total debt and book value of equity
Log assets	The natural logarithms of book assets in million CNY
Tangibility	Net value of plant, property, and equipment divided by total assets
Capex	Capital expenditure in year t scaled by the total assets in year *t-1*
Cash holdings	Cash and equivalents in year t divided by the total assets in year *t-1*
Log sales	The natural logarithms of sales in million CNY in year t
Sales growth	Sales in year t divided by sales in year *t-1* minus one.
ROA	Operating income before depreciation and amortization in year t scaled by the total assets in year *t-1*
Zscore private	Modified Altman Z-score applicable to emerging market private companies (Altman et al., 2017) $= 3.3 \times (EBIT/asset_{t-1}) + 1.0 \times (sales/asset_{t-1}) + 1.4 \times (retained\, earnings/asset_{t-1}) + 1.2 \times (working\, capital/asset_{t-1})$
Zscore public	Altman Z-score $= 3.3 \times (EBIT/asset_{t-1}) + 0.999 \times (sales/asset_{t-1}) + 1.4 \times (retained\, earnings/asset_{t-1}) + 1.2 \times (working\, capital/asset_{t-1}) + 0.6 \times (market\, value\, of\, equity/liability)$
Labor intensity	The number of total employees divided by real assets in million CNY in constant 2010 dollars in year *t-1*
ΔLabor	The change of the number of employees from year *t-1* to year t divided by real assets in million CNY in constant 2010 dollars
SOE	An indicator variable equal to one if the firm is a state-owned enterprise and zero otherwise
Private	An indicator variable equal to one if the firm is private and zero otherwise
MTB	Total assets minus book equity plus market equity scaled by total assets in year t
Workforce	The number of laborers in each city in year t
GDPpc	The logarithm of gross domestic product (GDP) per capita measured in CNY in each city in year t
Population	The logarithm of the population in each city in year t
Area	The logarithm of city area measured in km^2 in each city in year t
Import	An indicator variable equal to one if the net traffic outflow $(outflow - inflow)$ for each city before the 2023 Chinese Lunar New Year is positive and zero otherwise.

Size	The natural logarithms of inflation-adjusted to 2010 book assets in year *t-1*
Age	The number of years the firm is established
Size-Age (SA) index	$(-0.737 \times Size) + (0.043 \times Size^2) - (0.040 \times Age)$ (Hadlock and Pierce, 2010)

ONLINE APPENDICES

Property Rights, Labor Supply, and Firm Capital Structure

Chloe Yi Chen* Qing (Clara) Zhou† Di Bu‡

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IA.1 Delineation of Labor Market Areas in China

Delineating local labor markets is challenging in practice. The initial step involves selecting appropriate data that captures the journey-to-work experience. Previous studies rely on population census to acquire dweller-commuter pair observations that provide information on worker mobility between regions (Kropp and Schwengler, 2017). Consequently, this data enables a more precise depiction of local labor markets. Alternatively, the use of Baidu Qianxi migration data obtained during the 2023 Spring Festival could be a viable option. This dataset allows for the observation of workers' movements between cities, enabling the calculation of traffic volume and contributing to a better understanding of labor dynamics.

We employ the hierarchical agglomerative clustering (HAC) method utilized by Tolbert and Killian (1987) and Tolbert and Sizer (1996), due to its consistent and non-arbitrary approach in selecting a threshold value. We begin by computing the frequency matrix that captures the association between city i and city j (P_{ij}/P_{ji}):

$$P_{ij} = P_{ji} = \frac{(f_{ij} + f_{ji})}{min(l_1, l_j)}$$

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where f_{ij} is defined as the number of persons commuting from city i to city j, f_{ji} is defined as the number of persons commuting from city j to city i, l_i is the resident population of city i, and , l_j is the resident population of city j.[1] The cluster algorithm utilizes a matrix of distance (dissimilarity matrix D) coefficients: for any i, $D_{ii} = 0$. For $i \neq j$,

$$D_{ij} = D_{ji} = (1 - P_{ij})$$

The dissimilarity values (D_{ij}) range from zero to one. A lower value of D_{ij} signifies a stronger pair-wise commuting relationship between two cities, whereas a value of D_{ij} approaching one indicates very week commuting ties.[2]

Next, we apply a HAC analysis using average linkage and the dissimilarity matrix obtained above. This clustering algorithm groups cities together based on the strength of their commuting ties. However, the procedure outlined in Tolbert and Killian (1987) and Tolbert and Sizer (1996) does not provide clear guidance on selecting the 'optimal' cut-off point to cease merging clusters together. Although increasing the cut-off value can enhance the degree of live-work overlap, this would be balanced by a reduction in the cross-sectional sample size and a decrease in integration within each labor market. Previous studies have adopted a cut-off value of 0.98 as a common heuristic (e.g., Daisuke et al. (2020)).

To address this limitation, Bishop et al. (2021) introduce the use of wages growth and housing price growth to determine the cut-off point. They argue that these variables should demonstrate high correlation with each local labor market and low correlation across different labor markets. Accordingly, we compare the within-cluster correlation for wages growth and housing price growth at various cut-off points. Based on these metrics, a cut-off of 0.90 yielded reasonable results compared to other potential cut-off values. Additionally, when plotted on a map, our preferred local labour markets classifications appear reasonable. Figure IA.1 presents the dendrogram of our clustering results. The y-axis denoted the height of the tree diagram at which each node (city) is aggregated into a group. The blue dashed line indicates our cut-off value.

[1] China's seventh National Census was concluded in 2020, making the 2020 resident population the most current and appropriate data source for our study.

[2] Cities and their surroundings can be integrated and the dissimilarity between clusters may be underestimated. Following Imbert et al. (2022), we alleviate this concern by excluding migration within a 300km radius.

Table IA.1 provides a comprehensive list of 74 Labor Market Areas (LMAs) with administrative division codes (ADC) and the resident population in each city. Table IA.2 shows the summary statistics on the delineation of LMAs outlined in Table IA.1. The average resident population in a LMA is about 19 million. The largest LMA is Beijing-Shanghai area (LMA05) with a resident population exceeding 266 million distributed across 45 cities. Following closely, the second largest LMA is Shenzhen area (LMA07), with a resident population of over 230 million across 42 cities. The third largest LMA is Guangzhou area (LMA13) with a resident population of over 198 million spanning 38 cities. These findings corroborate the prevailing trend of workers being drawn to these first-tier mega cities due to the abundant job opportunities they offer.[3] The average number of cities within an LMA is 5, with at least half of the (41) LMAs being classified as isolate (single-city) LMAs. The composition of cities within LMAs varies based on their size, as classified by the National Development and Reform Commission's criteria for small, medium, big, or metropolitan cities.[4] Notably, LMAs tend to have a higher proportion of big cities compared to other size categories on average.

[3]See for example: https://country.eiu.com/article.aspx?articleid=1326926316&Country=China&topic=Economy and https://www.chinadaily.com.cn/a/202211/30/WS6386e6fca31057c47eba1e7a.html

[4]Based on the definitions provided by the National Development and Reform Commission, a small city is characterized by a population of less than 500,000, while a medium city is defined as having a population of at least 500,000 but not exceeding 1 million. A big city is denoted by a population of at least 1 million but not exceeding 5 million. Finally, a metropolitan area is identified as a city with a population exceeding 5 million. https://www.ndrc.gov.cn/xwdt/ztzl/xxczhjs/ghzc/201605/t20160509_971910.html

References

Bishop, J., E. Greenland, et al. (2021). *Is the Phillips Curve Still a Curve?: Evidence from the Regions*. Reserve Bank of Australia.

Daisuke, A., F. Taiyo, K. Daiji, S. Yukiko, et al. (2020). Commuting zones in japan. Technical report.

Imbert, C., M. Seror, Y. Zhang, and Y. Zylberberg (2022). Migrants and firms: Evidence from china. *American Economic Review 112*(6), 1885–1914.

Kropp, P. and B. Schwengler (2017). Stability of functional labour market regions. Technical report, IAB-Discussion Paper.

Tolbert, C. M. and M. Killian (1987). *Labor Market Areas for the United States. Washington, DC: Department of Agriculture*. Economic Research Service, Agricultural and Rural Economics Division.

Tolbert, C. M. and M. Sizer (1996). Us commuting zones and labor market areas: A 1990 update. Technical report.

Figures and Tables

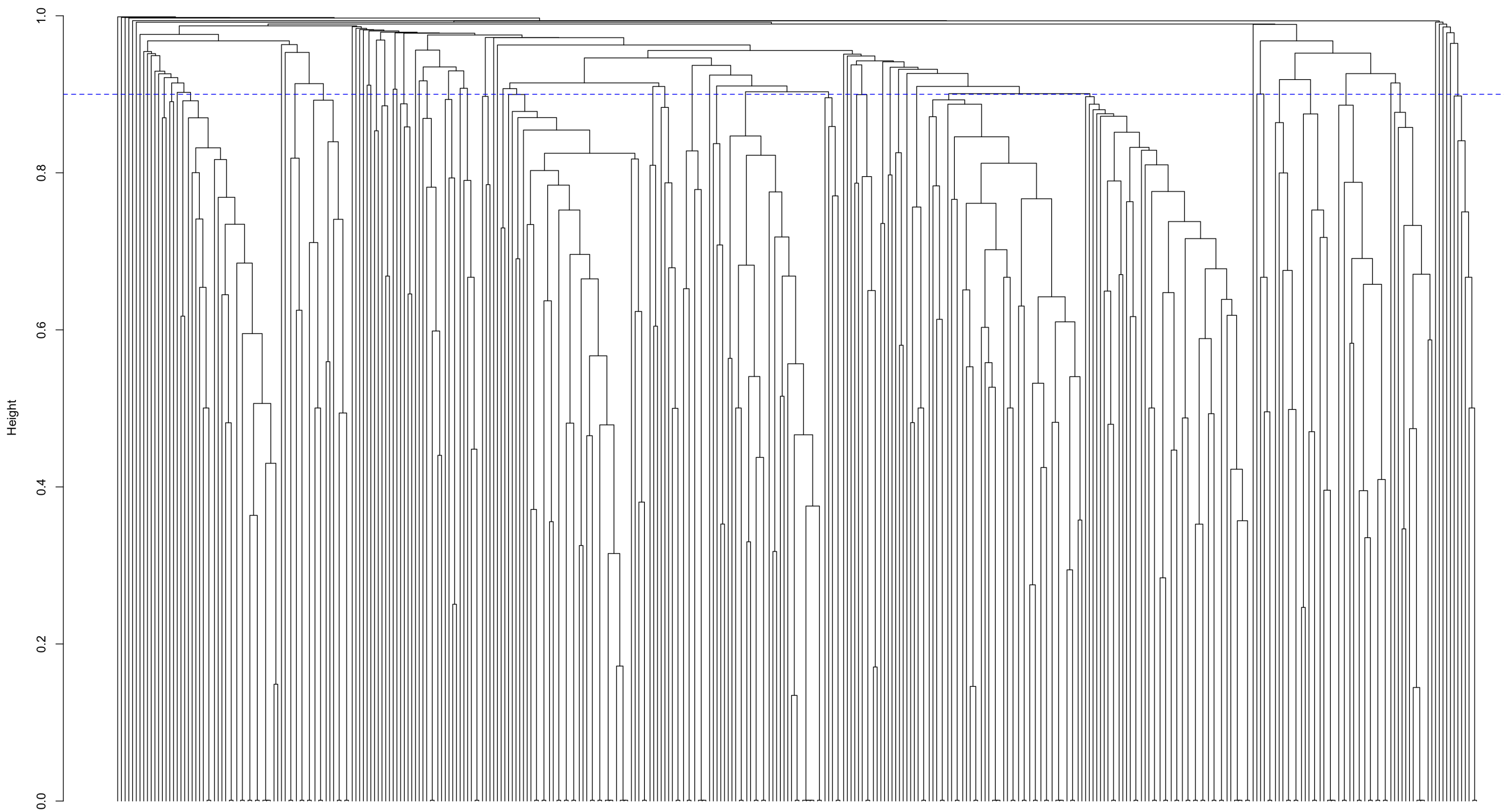

Figure IA.1. Cluster Dendrogram

This figure shows the dendrogram with the HAC method applied to the 2023 Baidu Qianxi Data. The blue dashed line signifies our cut-off value.

Table IA.1
China Labor Market Areas Based on 2023 Baidu Qianxi Data

LMA01

ADC	Area Name	2020 Population
230900	Qitaihe City	689,611
222400	Yanbian Korean Autonomous Prefecture	1,986,339
210400	Fushun City	1,861,372
211300	Chaoyang City	2,872,857
210500	Benxi City	1,326,018
210100	Shenyang City	9,070,093
231000	Mudanjiang City	2,290,208
220800	Baicheng City	1,551,378
231200	Suihua City	3,756,167
220500	Tonghua City	1,812,114
230700	Yichun City	878,881
220100	Changchun City	9,066,906
210900	Fuxin City	1,647,280
230300	Jixi City	1,502,060
230400	Hegang City	891,271
230800	Jiamusi City	2,156,505
231100	Heihe City	1,286,401
230200	Qiqihar City	4,067,489
152200	Hinggan League	1,416,929
230500	Shuangyashan City	1,208,803
220200	Jilin City	3,623,713
150700	Hulunbuir City	2,242,875
230100	Harbin City	10,009,854
220300	Siping City	1,814,733
232700	Da Hinggan Ling	331,276
230600	Daqing City	2,781,562
210200	Dalian City	7,450,785
Total		79,593,480

LMA02

ADC	Area Name	2020 Population
469005	Wenchang City	560,894
469006	Wanning City	545,992
469024	Lingshui County	420,594
460100	Haikou City	2,873,358
469002	Qionghai City	528,238
460400	Danzhou City	954,259
460300	Sansha City	2,333
Total		5,885,668

LMA03

ADC	Area Name	2020 Population
350400	Sanming City	2,486,450
Total		2,486,450

LMA04

ADC	Area Name	2020 Population
440700	Jiangmen City	4,798,090
440800	Zhanjiang City	6,981,236
469027	Ledong Li Autonomous County	464,435
469028	Lingshui Li Autonomous County	372,511
469029	Baoting Li and Miao Autonomous County	156,108
469007	Dongfang City	444,458
Total		13,216,838

LMA05

ADC	Area Name	2020 Population
140100	Taiyuan City	5,304,061
610900	Ankang City	2,493,436
410500	Anyang City	5,477,614
511500	Yibin City	4,588,804
610300	Baoji City	3,321,853
511900	Bazhong City	2,712,894
510800	Guangyuan City	2,305,657
610600	Yan'an City	2,282,581
410200	Kaifeng City	4,824,016
640500	Zhongwei City	1,067,336
410700	Xinxiang City	6,251,929
141000	Linfen City	3,976,481
140700	Jinzhong City	3,379,498
610800	Yulin City	3,624,750
610700	Hanzhong City	3,211,462
410300	Luoyang City	7,056,699
610500	Weinan City	4,688,744
410900	Puyang City	3,772,088
410800	Jiaozuo City	3,521,078
620400	Baiyin City	1,512,110
510700	Mianyang City	4,868,243
320500	Suzhou City	12,748,262
211400	Huludao City	2,434,194
420600	Xiangyang City	5,260,951
610100	Xi'an City	12,952,907
411000	Xuchang City	4,379,998
460200	Sanya City	1,031,396
140800	Yuncheng City	4,774,508
130500	Xingtai City	7,111,106
130400	Handan City	9,413,990
410100	Zhengzhou City	12,600,574
610200	Tongchuan City	698,322
411700	Zhumadian City	7,008,427
150200	Baotou City	2,709,378
110000	Beijing City	21,893,095
511300	Nanchong City	5,607,565
411200	Sanmenxia City	2,034,872
411300	Nanyang City	9,713,112
340100	Hefei City	9,369,881
310000	Shanghai City	24,870,895
640300	Wuzhong City	1,382,713
610400	Xianyang City	3,959,842
411400	Shangqiu City	7,816,831
620500	Tianshui City	2,984,659
120000	Tianjin City	13,866,009
Total		266,864,821

LMA06

ADC	Area Name	2020 Population
370500	Dongying City	2,193,518
371100	Rizhao City	2,968,365
370700	Weifang City	9,386,705
371700	Heze City	8,795,939
Total		23,344,527

LMA07

ADC	Area Name	2020 Population
441900	Dongguan City	10,466,625
330200	Ningbo City	9,404,283
340800	Anqing City	4,165,284
360900	Yichun City	5,007,702
341300	Suzhou City	5,324,476
430600	Yueyang City	5,051,922
320400	Changzhou City	5,278,121
422800	Enshi Tujia and Miao Autonomous Prefecture	3,456,136
361000	Fuzhou City	3,614,866
360200	Jingdezhen City	1,618,979
330100	Hangzhou City	11,936,010
341700	Chizhou City	1,342,764
350500	Quanzhou City	8,782,285
440300	Shenzhen City	17,560,061
330300	Wenzhou City	9,572,903
330500	Huzhou City	3,367,579
433100	Xiangxi Tujia and Miao Autonomous Prefecture	2,488,105
341100	Chuzhou City	3,987,054
330600	Shaoxing City	5,270,977
360400	Jiujiang City	4,600,276
330900	Zhoushan City	1,157,817
360300	Pingxiang City	1,804,805
340300	Bengbu City	3,296,408
330800	Quzhou City	2,276,184
360700	Ganzhou City	8,970,014
341600	Bozhou City	4,996,844
430100	Changsha City	10,047,914
341200	Fuyang City	8,200,264

LMA07

ADC	Area Name	2020 Population
340500	Ma'anshan City	2,159,930
360600	Yingtan City	1,154,223
421100	Huanggang City	5,882,719
341000	Huangshan City	1,330,565
411500	Xinyang City	6,234,401
320100	Nanjing City	9,314,685
350200	Xiamen City	5,163,970
331000	Taizhou City	6,622,888
360800	Ji'an City	4,469,176
411600	Zhoukou City	9,026,015
421200	Xianning City	2,658,316
361100	Shangrao City	6,491,088
611000	Shangluo City	2,041,231
330400	Jiaxing City	5,400,868
Total		230,996,733

LMA08

ADC	Area Name	2020 Population
331100	Lishui City	2,507,396
Total		2,507,396

LMA09

ADC	Area Name	2020 Population
210600	Dandong City	2,188,436
Total		2,188,436

LMA10

ADC	Area Name	2020 Population
520400	Anshun City	2,470,630
530700	Lijiang City	1,253,878
511600	Guang'an City	3,254,883
533100	Dehong Dai and Jingpo Autonomous Prefecture	1,315,709
431200	Huaihua City	4,587,594
510100	Chengdu City	20,937,757
532600	Wenshan Zhuang and Miao Autonomous Prefecture	3,503,218
530100	Kunming City	8,460,088
530600	Zhaotong City	5,092,611
530800	Pu'er City	2,404,954
530300	Qujing City	5,765,775
530900	Lincang City	2,257,991
532300	Chuxiong Yi Autonomous Prefecture	2,416,747
520500	Bijie City	6,899,636
530400	Yuxi City	2,249,502
532500	Honghe Hani and Yi Autonomous Prefecture	4,478,422
532800	Xishuangbanna Dai Autonomous Prefecture	1,301,407
520100	Guiyang City	5,987,018
520300	Zunyi City	6,606,675
330700	Jinhua City	7,050,683
520600	Tongren City	3,298,468
522300	Qianxinan Buyei and Miao Autonomous Prefecture	3,015,112
530500	Baoshan City	2,431,211
520200	Liupanshui City	3,031,602
513400	Liangshan Yi Autonomous Prefecture	4,858,359
532900	Dali Bai Autonomous Prefecture	3,337,559
Total		118,267,489

LMA11

ADC	Area Name	2020 Population
621100	Dingxi City	2,524,097
620800	Pingliang City	1,848,607
621000	Qingyang City	2,179,716
620700	Zhangye City	1,131,016
622900	Linxia Hui Autonomous Prefecture	2,109,750
620600	Wuwei City	1,464,955
659004	Wujiaqu City	98,990
620900	Jiuquan City	1,055,706
620300	Jinchang City	438,026
640100	Yinchuan City	2,859,074
152900	Alxa League	262,361
620100	Lanzhou City	4,359,446
650500	Hami City	673,383
620200	Jiayuguan City	312,663
Total		21,317,790

LMA12

ADC	Area Name	2020 Population
371000	Weihai City	2,906,548
371300	Linyi City	11,018,365
370900	Tai'an City	5,472,217
370100	Jinan City	9,202,432
370300	Zibo City	4,704,138
370600	Yantai City	7,102,116
Total		40,405,816

LMA13

ADC	Area Name	2020 Population
451400	Chongzuo City	2,088,692
430700	Changde City	5,279,102
440100	Guangzhou City	18,676,605
430800	Zhangjiajie City	1,517,027
441300	Huizhou City	6,042,852
442000	Zhongshan City	4,418,060
445200	Jieyang City	5,577,814
451300	Laibin City	2,074,611
450200	Liuzhou City	4,157,934
450300	Guilin City	4,931,137
441400	Meizhou City	3,873,239
450400	Wuzhou City	2,820,977
431100	Yongzhou City	5,289,824
451200	Hechi City	3,417,945
441800	Qingyuan City	3,969,473
445100	Chaozhou City	2,568,387
450900	Yulin City	5,796,766
440400	Zhuhai City	2,439,585
451000	Baise City	3,571,505
430900	Yiyang City	3,851,564
431300	Loudi City	3,826,996
441200	Zhaoqing City	4,113,594
421000	Jingzhou City	5,231,180
445300	Yunfu City	2,383,350
430400	Hengyang City	6,645,243
450800	Guigang City	4,316,262
451100	Hezhou City	2,007,858
430500	Shaoyang City	6,563,520
431000	Chenzhou City	4,667,134
500000	Chongqing City	32,054,159
450700	Qinzhou City	3,302,238
450600	Fangchenggang City	1,046,068
441700	Yangjiang City	2,602,959
440600	Foshan City	9,498,863
522600	Qiandongnan Miao and Dong Autonomous Prefecture	3,758,622
522700	Qiannan Buyei and Miao Autonomous Prefecture	3,494,385
450500	Beihai City	1,853,227
450100	Nanning City	8,741,584
Total		198,470,341

LMA14

ADC	Area Name	2020 Population
150900	Ulanqab City	1,706,328
640200	Shizuishan City	751,389
150600	Ordos City	2,153,638
640400	Guyuan City	1,142,142
140200	Datong City	3,105,591
Total		8,859,088

LMA15

ADC	Area Name	2020 Population
510400	Panzhihua City	1,212,203
511100	Leshan City	3,160,168
511800	Ya’an City	1,434,603
511000	Neijiang City	3,140,678
Total		8,947,652

LMA16

ADC	Area Name	2020 Population
469001	Wuzhishan City	112,269
Total		112,269

LMA17

ADC	Area Name	2020 Population
150800	Bayannur City	1,538,715
130700	Zhangjiakou City	4,118,908
130800	Chengde City	3,354,444
150300	Wuhai City	556,621
130100	Shijiazhuang City	11,235,086
130300	Qinhuangdao City	3,136,879
150400	Chifeng City	4,035,967
150500	Tongliao City	2,873,168
152500	Xilingol League	1,107,075
130600	Baoding City	11,437,217
150100	Hohhot City	3,446,100
130200	Tangshan City	7,717,983
Total		54,558,163

LMA18

ADC	Area Name	2020 Population
652300	Changji Hui Autonomous Prefecture	1,613,585
650100	Urumqi City	4,054,369
659001	Shihezi City	661,300
654000	Ili Kazakh Autonomous Prefecture	2,848,393
654300	Altay Prefecture	668,587
650200	Karamay City	490,348
659005	Beitun City	74,196
652700	Bortala Mongol Autonomous Prefecture	488,198
659007	Shuanghe City	133,200
659003	Tumxuk City	245,790
654200	Tacheng Prefecture	1,138,638
Total		12,416,604

LMA19

ADC	Area Name	2020 Population
429006	Tianmen City	1,158,640
420900	Xiaogan City	4,270,371
430200	Zhuzhou City	3,902,738
420100	Wuhan City	12,326,518
429021	Shennongjia Forestry District	66,571
429004	Xiantao City	1,134,715
420300	Shiyan City	3,209,004
Total		26,068,557

LMA20

ADC	Area Name	2020 Population
540200	Shigatse City	798,153
659009	Kunyu City	57,000
540600	Nagqu City	504,838
652900	Aksu Prefecture	2,714,422
659002	Aral City	295,950
542500	Ngari Prefecture	123,281
653000	Kyrgyz Autonomous Prefecture	622,222
650400	Turpan City	693,988
653200	Hotan Prefecture	2,504,718
653100	Kashgar Prefecture	4,496,377
Total		12,810,949

LMA21

ADC	Area Name	2020 Population
350700	Nanping City	2,680,645
360100	Nanchang City	6,255,007
Total		8,935,652

LMA22

ADC	Area Name	2020 Population
321300	Suqian City	4,986,192
320200	Wuxi City	7,462,135
320700	Lianyungang City	4,599,360
341500	Lu'an City	4,393,699
320600	Nantong City	7,726,635
Total		29,168,021

LMA23

ADC	Area Name	2020 Population
659008	Kekedala City	256,551
Total		256,551

LMA24

ADC	Area Name	2020 Population
141100	Lvliang City	3,398,431
Total		3,398,431

LMA25

ADC	Area Name	2020 Population
350900	Ningde City	3,146,789
441500	Shanwei City	2,672,819
350600	Zhangzhou City	5,054,328
350800	Longyan City	2,723,637
Total		13,597,573

LMA26

ADC	Area Name	2020 Population
469021	Ding'an County	284,690
Total		284,690

LMA27

ADC	Area Name	2020 Population
420500	Yichang City	4,017,607
420700	Ezhou City	1,079,353
420200	Huangshi City	2,469,079
Total		7,566,039

LMA28

ADC	Area Name	2020 Population
341800	Xuancheng City	2,500,063
Total		2,500,063

LMA29

ADC	Area Name	2020 Population
469022	Tunchang County	255,335
Total		255,335

LMA30

ADC	Area Name	2020 Population
540500	Shannan City	354,035
Total		354,035

LMA31

ADC	Area Name	2020 Population
410400	Pingdingshan City	4,987,137
Total		4,987,137

LMA32

ADC	Area Name	2020 Population
131000	Langfang City	5,464,087
Total		5,464,087

LMA33

ADC	Area Name	2020 Population
652800	Bayingolin Mongol Autonomous Prefecture	1,613,979
630200	Haidong City	1,358,471
632200	Haibei Tibetan Autonomous Prefecture	265,322
632500	Hainan Tibetan Autonomous Prefecture	446,996
632800	Haixi Mongol and Tibetan Autonomous Prefecture	468,216
632700	Yushu Tibetan Autonomous Prefecture	425,199
630100	Xining City	2,467,965
Total		7,046,148

LMA34

ADC	Area Name	2020 Population
320300	Xuzhou City	9,083,790
321200	Taizhou City	4,512,762
321100	Zhenjiang City	3,210,418
Total		16,806,970

LMA35

ADC	Area Name	2020 Population
371400	Dezhou City	5,611,194
370400	Zaozhuang City	3,855,601
370800	Jining City	8,357,897
371500	Liaocheng City	5,952,128
370200	Qingdao City	10,071,722
Total		33,848,542

LMA36

ADC	Area Name	2020 Population
510600	Deyang City	3,456,161
Total		3,456,161

LMA37

ADC	Area Name	2020 Population
140900	Xinzhou City	2,689,668
140500	Jincheng City	2,194,545
130900	Cangzhou City	7,300,783
Total		12,184,996

LMA38

ADC	Area Name	2020 Population
533300	Nujiang Lisu Autonomous Prefecture	552,694
540100	Lhasa City	867,891
540300	Changdu City	760,966
540400	Linzhi City	238,936
513300	Garzê Tibetan Autonomous Prefecture	1,107,431
533400	Deqen Tibetan Autonomous Prefecture	387,511
510900	Suining City	2,814,196
Total		6,729,625

LMA39

ADC	Area Name	2020 Population
321000	Yangzhou City	4,559,797
Total		4,559,797

LMA40

ADC	Area Name	2020 Population
360500	Xinyu City	1,202,499
Total		1,202,499

LMA41

ADC	Area Name	2020 Population
469026	Changjiang Li Autonomous County	232,124
Total		232,124

LMA42

ADC	Area Name	2020 Population
140600	Shuozhou City	1,593,444
140400	Changzhi City	3,180,884
Total		4,774,328

LMA43

ADC	Area Name	2020 Population
220700	Songyuan City	2,252,994
220600	Baishan City	968,373
Total		3,221,367

LMA44

ADC	Area Name	2020 Population
419001	Jiyuan City	727,265
Total		727,265

LMA45

ADC	Area Name	2020 Population
659006	Tiemenguan City	231,600
Total		231,600

LMA46

ADC	Area Name	2020 Population
632600	Golog Tibetan Autonomous Prefecture	215,573
623000	Gannan Tibetan Autonomous Prefecture	691,808
513200	Aba Tibetan and Qiang Autonomous Prefecture	822,587
621200	Longnan City	2,407,272
Total		4,137,240

LMA47

ADC	Area Name	2020 Population
440500	Shantou City	5,502,031
350300	Putian City	3,210,714
Total		8,712,745

LMA48

ADC	Area Name	2020 Population
441600	Heyuan City	2,837,686
440900	Maoming City	6,174,050
440200	Shaoguan City	2,855,131
Total		11,866,867

LMA49

ADC	Area Name	2020 Population
340600	Huaibei City	1,970,265
340200	Wuhu City	3,644,420
Total		5,614,685

LMA50

ADC	Area Name	2020 Population
510500	Luzhou City	4,254,149
511400	Meishan City	2,955,219
350100	Fuzhou City	8,291,268
510300	Zigong City	2,489,256
511700	Dazhou City	5,385,422
Total		23,375,314

LMA51

ADC	Area Name	2020 Population
340400	Huainan City	3,033,528
Total		3,033,528

LMA52

ADC	Area Name	2020 Population
320800	Huai'an City	4,556,230
Total		4,556,230

LMA53

ADC	Area Name	2020 Population
430300	Xiangtan City	2,726,181
Total		2,726,181

LMA54

ADC	Area Name	2020 Population
371600	Binzhou City	3,928,568
Total		3,928,568

LMA55

ADC	Area Name	2020 Population
411100	Luohe City	2,367,490
Total		2,367,490

LMA56

ADC	Area Name	2020 Population
429005	Qianjiang City	886,547
Total		886,547

LMA57

ADC	Area Name	2020 Population
469023	Chengmai County	497,953
Total		497,953

LMA58

ADC	Area Name	2020 Population
469030	Qiongzhong Li and Miao Autonomous County	179,586
Total		179,586

LMA59

ADC	Area Name	2020 Population
469025	Baisha Li Autonomous County	164,699
Total		164,699

LMA60

ADC	Area Name	2020 Population
320900	Yancheng City	6,709,629
Total		6,709,629

LMA61

ADC	Area Name	2020 Population
211100	Panjin City	1,389,691
Total		1,389,691

LMA62

ADC	Area Name	2020 Population
420800	Jingmen City	2,596,927
Total		2,596,927

LMA63

ADC	Area Name	2020 Population
210800	Yingkou City	2,328,582
220400	Liaoyuan City	996,903
Total		3,325,485

LMA64

ADC	Area Name	2020 Population
131100	Hengshui City	4,212,933
Total		4,212,933

LMA65

ADC	Area Name	2020 Population
512000	Ziyang City	2,308,631
Total		2,308,631

LMA66

ADC	Area Name	2020 Population
211000	Liaoyang City	1,604,580
Total		1,604,580

LMA67

ADC	Area Name	2020 Population
211200	Tieling City	2,388,294
Total		2,388,294

LMA68

ADC	Area Name	2020 Population
340700	Tongling City	1,311,726
Total		1,311,726

LMA69

ADC	Area Name	2020 Population
210700	Jinzhou City	2,703,853
Total		2,703,853

LMA70

ADC	Area Name	2020 Population
140300	Yangquan City	1,318,505
Total		1,318,505

LMA71

ADC	Area Name	2020 Population
421300	Suizhou City	2,047,923
Total		2,047,923

LMA72

ADC	Area Name	2020 Population
210300	Anshan City	3,325,372
Total		3,325,372

LMA73

ADC	Area Name	2020 Population
410600	Hebi City	1,565,973
Total		1,565,973

LMA74

ADC	Area Name	2020 Population
632300	Huangnan Tibetan Autonomous Prefecture	276,215
Total		276,215

Table IA.2
Summary Statistics

This table reports the descriptive statistics for China labor market areas. Column (1) indicates the number of areas, columns (2) and (3) show the means and standard deviations, and columns (4) to (6) provide the 25% percentile, median, and 75% percentile.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	N	Mean	SD	Minimum	25%	Median	75%	Maximum
Resident population	74	19,057,317	48,027,751	112,269	1,604,580	4,032,904	12,184,996	266,864,821
City composition	74	5	9	1	1	1	5	45
Number of small cities	74	0.5	1.1	0	0	0	1	5
Number of medium cities	74	0.4	0.9	0	0	0	0	4
Number of big cities	74	2.9	5.5	0	1	1	2	26
Number of metropolitan	74	1.2	3.7	0	0	0	1	22