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Infrastructure as Financial Accelerators:

Evidence from Subway Construction in Chinese Cities[1]

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ABSTRACT: We propose and test an unexplored collateral channel for government infrastructural investment to crowd in private-sector financing by exploiting the variations created by China's subway expansion. We purposefully build a geo-financial dataset that links private firms with their nearest new subway stations. Using a firm-level stacked difference-in-differences research design, we find that the introduction of a new subway station is associated with an increase of 4.30

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percentage points — equivalent to 12.44% of the sample mean — in the debt/asset ratio of private firms located within a 1-kilometer radius of the station. We also find that the values of firms' production structures and land holdings have increased following the opening of a nearby subway station and higher values of these assets increase firms' external financing.
Keywords: government investment; financial accelerator; subways; private-firm financing; collateral values

JEL Classifications: G14; G18; G34

1. Introduction

Existing literature has extensively explored the costs associated with government spending, highlighting its crowding-out effects on private investment.[2] However, when it is directed toward infrastructural construction (e.g., public roads, highways, railways, and subways), government investment may increase the economic value of nearby private assets served by such infrastructure. In an environment featuring credit constraints, such investment may create a financial-accelerator effect, enabling the private sector to borrow more by pledging higher-valued collateral. This crowding-in effect, although secondary in nature, can lead to significant pro-cyclical consequences in a rapidly urbanizing economy with financial frictions, much like the financial accelerator effects observed in mature economies (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Bernanke et al., 1999).[3]

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[2] For representative studies, see Bai et al. (2016), Huang et al. (2020), Chen et al. (2020), Gao et al. (2021), and Fay et al. (2021).

[3] The financial accelerator refers to a mechanism through which initial economic shocks are amplified via credit markets due to underlying financial frictions. It is typically formalized in two canonical frameworks. The first highlights the external finance premium, which arises from information asymmetries between borrowers and lenders. This premium, inversely related to a firm's net worth, rises when adverse shocks weaken profitability and balance sheets, thus raising borrowing costs, tightening credit, and amplifying the initial disturbance (Bernanke and Gertler, 1989; Bernanke et al., 1999). The second centers on collateral constraints, where borrowing capacity is linked to asset values through loan-to-value ratios. During downturns, declining asset

In this study, we exploit China's large-scale subway expansion in the aftermath of the 2008 Beijing Olympic Games to identify the financial-accelerator effect of government investment. We focus on subway investment as it provides an ideal quasi-natural experiment for government investment. For firms already operating in a given location, the introduction of a subway station is an external shock, which allows us to employ a distance-based difference-in-differences (DID) research design to study the impact of government investment on firm financing. Meanwhile, subway systems are typically located in densely populated urban areas and stimulate high-density, high-value commercial activities in adjacent areas. This spatial concentration makes our distance-based DID analysis meaningful as the treated firms (i.e., those located near a subway station) and the control firms (i.e., those located farther away from any subway station) are not inherently different except for their distances to any subway stations.

Subway systems may create a financial-accelerator effect for the private sector by increasing the market values of firms' land and buildings. For one thing, by providing convenient, reliable, and affordable station-to-station commuting services, subways substantially extend feasible commuting distances and reduce travel time. This improvement enhances the attractiveness of firms located close to subway stations for their potential employees, thereby increasing firms' land and building values. More importantly, commercial activities tend to agglomerate around subway stations, increasing demand for nearby land and buildings. Given the relatively inelastic supply of urban land and structures, this surge in demand is largely capitalized into asset prices, resulting in substantial appreciation of land and building values (Baum-Snow and Kahn, 2000; Bowes and

prices erode collateral, limit credit access, and trigger deleveraging, further suppressing investment and deepening recessions (Kiyotaki and Moore, 1997).

Ihlanfeldt, 2001). Taken together, these effects strengthen the collateral base of nearby firms, which, in turn, relax their borrowing constraints and improve their access to external financing.

We focus on China's private firms. Over the past few decades, China's private sector has expanded rapidly and serves as a critical engine of national economic growth.[4] Despite its importance, private firms in China face severe financing constraints. The credit market is characterized by ownership-based discrimination; state-owned enterprises (SOEs) enjoy preferential access to external financing, whereas private firms are often required to pledge additional collateral to obtain external financing (Song et al., 2011; Whited and Zhao, 2021; Shi et al., 2023; Hu et al., 2025). Chronic deficiencies in pledgeable collateral (usually land and production structures) substantially constrain private firms' access to credit. Government infrastructure investment has the potential to alleviate these constraints by enhancing the values of private firms' collateral assets, but this role has received limited attention in both academic research and policy discussions. Our study intends to fill this gap.

To conduct our study, we manually collect data on subway lines and stations across Chinese cities. Then we sample approximately 300,000 private firms from China's annual tax surveys that provide detailed financial data for surveyed firms from 2007 to 2016. Each firm is matched to its nearest subway station and the distance between the firm and the nearest station is measured. In our baseline specification, we restrict the sample to private firms located within a 5-kilometer radius of a newly opened subway station, defining the treatment group (control group) as firms located within (outside) a 1-kilometer radius of a newly opened subway station. Then we estimate a firm-level stacked DID model to explore the impact of subway infrastructure on private firms'

[4] According to official statistics, the private sector accounts for over 90% of enterprises and contributes more than 50% of tax revenues, 60% of GDP, 70% of innovation output, and 80% of employment. See www.gov.cn/xinwen/2019-01/14/content_5357602.htm.

financing. We find that the debt/asset ratio is 4.30 percentage points — equivalent to 12.44% of the sample mean — higher in the treatment group than in the control group. This finding remains robust to alternative measures of private firms' financing, propensity score matching, alternative definitions of the treatment and control groups, subsample analyses, and placebo tests. Moreover, we find that the introduction of a new subway station increases the values of private firms' production structures and land holdings if they happen to possess those two kinds of assets. Additional analysis reveals that the introduction of subway stations significantly raises private firms' purchase of land and construction/purchase of production structures. These results indicate that subway infrastructure enhances private firms' financing capacity by increasing the values of their collateral assets.

Our paper contributes to two strands of literature. First, we find empirical evidence for a novel crowding-in effect of government investment operating through the collateral channel. Although this crowding-in effect is second-order and does not necessarily offset the first-order crowding-out effect that is traditionally associated with government investment, our finding provides a more nuanced perspective on government spending. As the macro-financial literature has revealed, the financial accelerator can substantially amplify pro-cyclical fluctuations in the economy. Government-sponsored infrastructure investment is widely viewed as one of China's secrets of fast economic growth. Our findings indicate that, beyond its direct contribution to growth, infrastructure investment boosts growth via the credit channel. On the flip side, a sharp reduction in government spending on infrastructure can lead to economic contraction by weakening firms' financing capacity. This contraction can be particularly severe if the reduction in government spending is part of a larger deleveraging policy, as in the case of China's nationwide deleveraging campaign in 2017-2019 (Hu et al., 2025). As China's model of infrastructure investment is now being recommended to other countries, it is worthwhile for policymakers around the world to understand the potential pro-cyclical effects of large-scale projects. Through these results, we contribute to the burgeoning literature on the real economic impacts of public investment.[5]

Second, we expand the scope of the literature on private-sector financing. In contrast to existing studies that focus on institutional and macro-financial determinants of private firm financing (e.g., bank credit constraints, property rights, and political connections) (Paravisini, 2008; Huang et al., 2020; Berkowitz and Lin, 2015; Ding et al., 2023; Wen et al., 2024), our study highlights the role of government investment in shaping firms' financing conditions. While government investment may crowd out private-sector investment at the macro level, private firms located in regions benefiting from government investment could enjoy improved financing conditions through the financial-accelerator channel. These insights are especially relevant for emerging economies where infrastructure deficits coexist with severe financial frictions. As demonstrated by China's experience, economic takeoff can be accelerated if a country starts with some key geographic regions. Our results thus offer a potential pathway for countries to break the vicious cycle of underinvestment in public infrastructure and credit rationing in these key geographic regions.

The remainder of the paper proceeds as follows. Section 2 introduces China's subway expansion in the aftermath of the 2008 Beijing Olympic Games. Section 3 describes the data and outlines the empirical methodology. Section 4 presents the main results. Section 5 explores the potential mechanisms. Section 6 concludes the paper.

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[5] For representative studies, see Duranton and Turner (2011), Garcia-López et al. (2015), Donaldson and Hornbeck (2016), Agrawal et al. (2017), Asher and Novosad (2020), Heblich et al. (2020), Huang et al. (2020), Dinlersoz and Fu (2022), and Barwick et al. (2024).

2. China's subway expansion

2.1. An account of the expansion

Subways are important urban transportation facilities in modern cities. China's subway system has undergone more than five decades of development. The first subway line, completed in 1965 and initially designed for military purposes, was opened to the public in 1969. However, for the subsequent two decades, despite rapid demographic growth and accelerated urbanization, the expansion of China's subway system was slow due to limited economic capacity, technological constraints, and stringent top-down governmental approval procedures. By 2000, only four cities (i.e., Beijing, Shanghai, Guangzhou, and Tianjin) had subway systems, comprising seven lines and 114 stations, with a combined network length of fewer than 150 kilometers and annual passenger ridership below one billion.

The phase of rapid subway expansion began in 2007, a year prior to the 2008 Beijing Olympic Games, when Beijing expedited subway construction to improve connectivity between major stadiums and residential districts. In response to the 2007-2008 global financial crisis, the Chinese government introduced a RMB 4 trillion (approximately US$586 billion) stimulus package. As part of the package, subway construction entered a new phase of rapid expansion.[6] The goal was to add 10,000 kilometers to the urban rail transit system by 2025.[7] By the end of 2024, this

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[6] Of the total funds, RMB 1.87 trillion (46.8%) was allocated to infrastructure investment, with RMB 1.5 trillion directed toward transport and energy systems (e.g., railways, subways, highways, airports, water conservancy, and urban power grids) and RMB 0.37 trillion allocated for rural infrastructure. The remaining resources (53.2%) were distributed across other priority areas, including RMB 1 trillion for post-earthquake reconstruction, RMB 0.40 trillion for affordable housing, RMB 0.15 trillion for health and education, and RMB 0.58 trillion for environmental protection and technological innovation. See www.gov.cn/gzdt/2009-03/06/content_1252229.htm.

[7] 14th Five-Year Plan for the Development of a Modern Comprehensive Transportation System. See www.gov.cn/zhengce/zhengceku/2022-01/18/content_5669049.htm.

ambitious goal was nearly achieved, with 41 cities operating more than 258 lines and approximately 6,300 stations, totaling around 9,306 kilometers of track. In parallel, annual subway ridership increased to approximately 31 billion trips. Figure 1 and Appendix Figure A1 illustrate the rapid expansion of China's subway networks between 2000 and 2024.

[Figure 1 about here]

Subways have become a major mode of urban transport in Chinese cities due to their technological and economic advantages, including high speed, safety, reliability, large passenger capacity, punctuality, and relatively low fares. According to the Beijing Transport Institute (2015), subway systems accounted for approximately 15% of total non-walking commuting trips and nearly 40% of total passenger-kilometers traveled in 2014. On average, a subway journey covered about 15 kilometers and took approximately 34 minutes, including waiting time (see Appendix Figure A2). The average subway speed (approximately 26.47 kilometers per hour) was comparable to that of private vehicles and considerably faster than buses and bicycles. Firms located close to subway stations thus enjoy a transport-accessibility premium, which is manifested by increased customer flows, higher building values, and appreciation in surrounding land prices.

However, subway construction is highly capital-intensive. Data from the China Association of Metros (2022) indicate an average construction cost of RMB 0.7-1.0 billion per kilometer, implying RMB 20-40 billion for a standard 30-40 km line.[8] These expenditures are ultimately borne by governments through direct budgetary spending or the accumulation of public debt (Chen et al., 2020; Huang et al., 2020). To address the substantial funding gap between fiscal revenues and the enormous capital requirements of subway projects, local governments have relied heavily on Local Government Financing Vehicles (LGFVs) — commercial entities resembling state-

[8] See www.camet.org.cn/.

owned enterprises — as quasi-fiscal instruments to raise funds without formally recording budget deficits. By 2023, the interest-bearing debts of LGFVs had surged to RMB 61.56 trillion, of which bank loans accounted for RMB 41.32 trillion (see Appendix Figure A3). This massive expansion of government-sponsored debt undoubtedly puts pressure on private-sector borrowing capacity, as the crowding-out literature has proven (Huang et al., 2020; Wen et al., 2024).[9] However, as a substantial portion of this debt has financed infrastructural construction, the private sector may simultaneously benefit through the financial-accelerator channel proposed by this paper.

2.2. Regional distribution of subways and private firms

In China, a city must obtain approval from the central government if it intends to build a new subway line. A centrally appointed evaluation committee conducts a comprehensive assessment of the city's fiscal capacity, regional gross domestic product (GDP), size of population and its projected growth, and other relevant factors.[10] Consequently, the distribution of subway systems across China has been highly uneven (see Figure 1). First-tier cities such as Shanghai, Beijing, and Shenzhen feature dense and well-developed subway networks, whereas many western cities have only limited or fragmented systems. Within cities, subway networks have expanded from single-line systems to more complex radial-circular networks. Correspondingly, subway stations have evolved from isolated transport facilities into integrated intermodal hubs connecting railways,

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[9] LGFVs enjoy structural advantages in accessing bank credit. First, they are typically well-capitalized, benefiting from the transfer of high-quality assets from local governments (e.g., land-use rights, land-sale revenues, and other valuable state-owned resources), which function as ample collateral for bank lending. Second, LGFVs frequently benefit from explicit guarantees or implicit backing from local governments, enhancing their perceived creditworthiness among financial institutions. Third, as government-established and government-controlled entities undertaking predominantly public investment projects, LGFVs are widely regarded as low-risk borrowers. Even when repayment difficulties arise, loan officers at large state-owned commercial banks face limited accountability, further reinforcing LGFVs' preferential access to credit.

[10] Cities applying for subway construction must meet the following criteria: general public fiscal budget revenue should exceed RMB 30 billion, regional gross domestic product (GDP) should be above RMB 300 billion, and the urban population should be over 3 million. See www.gov.cn/zhengce/content/2018-07/13/content_5306202.htm.

airports, and major bus terminals.

An important component of our study is matching private firms with their nearest subway stations. Generally, cities with subway systems exhibit higher firm density and wider geographical coverage, particularly major metropolitan areas such as Beijing and Shanghai. Within these cities, firms tend to agglomerate along subway corridors or around subway stations. Figure 2 illustrates the distribution of private firms relative to subway lines in Beijing and Shanghai between 2007 and 2016. In both cities, firm density was highest in downtown areas where subway lines were also dense, and it declined toward suburban areas. In Beijing, there was no clear sign of firms agglomerating along subway lines. This was also true in downtown Shanghai. By contrast, in suburban Shanghai, firms tended to locate around subway lines and near their terminal stations.[11]

[Figure 2 about here]

A crucial challenge for our identification strategy is whether the distribution of subway stations is endogenous to economic and commercial activities. If subway stations are disproportionately constructed in areas that are already more economically active, the estimated effects of subway stations may be created by the pre-existing prosperous activities, not the stations themselves. The agglomeration of firms that we've found in Figure 2 partially alleviates the concern (for example, it is hard to imagine that firms were first established along a subway line in suburban Shanghai and then a subway line was built along it). But we will carefully design our empirical strategy to address the endogeneity issue.

3. Data and methodology

[11] These differences reflect the two cities' distinct approaches to urban planning. Beijing has expanded in multiple directions without clearly defined satellite cities, whereas Shanghai has deliberately developed several satellite cities and connected them with the city center through highways and subway systems.

3.1. Data sources and sample selection

The data used in our study cover the period from 2007 to 2016.[12] Firm-level data are drawn from the National Tax Survey Database (NTSD), a unique, comprehensive, and largely underexplored dataset jointly administered by the Ministry of Finance and the State Taxation Administration, with local tax authorities conducting the survey through a stratified random sampling strategy. The NTSD collects and rigorously verifies detailed information on tax-paying entities, including their characteristics, operations, and financial performance, encompassing over 400 high-precision indicators, including taxes, balance sheets, income statements, and cash flow statements.[13] Pertinent to our study, subsidiaries of large companies are recorded separately, so we can treat each firm as an independent case in our analysis. In addition, the NTSD covers above-scale firms as well as small, medium, and micro enterprises across all prefecture-level cities and all sectors, exhibiting strong representativeness at both the regional and sectoral levels, thereby making it superior to other widely used datasets such as the Annual Survey of Industrial Firms. Because the NTSD does not report firms' geographic coordinates, we match NTSD to official business registration records to retrieve firms' registered addresses. We then use both the

[12] The NTSD started in 2007. The latest publicly available data are for 2016.

[13] There are four key technical and institutional safeguards that enhance the accuracy of the NTSD. First, the electronic submission system incorporates built-in validation mechanisms that automatically check for internal consistency across key variables and ensure the completeness of reported information. Second, local tax authorities cross-verify firms' survey responses against official tax filings before final submission, raising the cost and risk of misreporting core variables such as tax liabilities, assets, investment, inputs, and employment. Third, China's Value-Added Tax (VAT) credit-invoice system requires firms to issue tax invoices for all sales and claim input credits for purchases and fixed assets, requiring fixed-asset transactions to be supported by verifiable VAT invoices, thereby deterring the overreporting of assets. Fourth, the nationwide "Golden Tax Project," operational since 1994, electronically generates and monitors VAT invoices via secure anti-counterfeiting and inspection subsystems, enabling real-time verification and thereby improving data integrity.

registered address and firm name to obtain firms' geographic coordinates via geocoding APIs provided by Amap (Gaode Maps) and Baidu Maps.[14]

We define subway systems to include both above-ground rail systems and underground subways, but exclude trams. To complement the firm-level data, we manually collect annual information on each city's subway system, including subway lines, stations, and the start and completion dates of their construction, from official metro and government websites.[15] These data are cross-validated with publicly available sources such as Wikipedia and Baidu Encyclopedia to ensure completeness and accuracy. We then use the Amap (Gaode Maps) Geocoding API to extract the geographic coordinates of each station. In total, we obtain information on 6,260 stations across 258 subway lines. Of these, 381 stations were already operational at the start of our sample period. Among them, 293 stations remained unchanged, with no new lines serving them during the sample period, while 88 stations were connected to newly added lines. In contrast, construction of the remaining 5,879 stations began during the sample period, but only 1,952 were opened during the sample period, while the remaining 3,887 had not yet opened by the end of the sample period.[16] Accordingly, our analytical sample consists of 2,333 stations that were operational at any point between 2007 and 2016, distributed across 27 mainland Chinese cities. Appendix Table A1 presents the details of subway line operations in China (Stations completed before 2007 do not

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[14] We primarily utilize the Amap (Gaode Maps) API to geocode firm addresses due to its higher queries per second (QPS) capacity. For addresses that cannot be geocoded using Amap, we supplement the process using the Baidu Maps API. Geocoding results from both platforms are then merged and standardized to the WGS-84 coordinate system to ensure spatial consistency. To improve computational efficiency, we implement multithreading techniques during data processing. The combined use of both platforms also facilitates cross-validation, thereby enhancing the completeness and reliability of the geocoded data.

[15] For example, www.urbanrail.net/.

[16] All station statistics treat stations separately from subway lines. That is, when multiple lines serve a station, that station is recorded only once.

contribute to our estimation, as firms located within 1 kilometer of a station in 2007 are automatically excluded).

A firm's distance to the nearest subway station is measured by the geodesic distance between its registered address and the nearest operational subway station. To compute this distance, we employ the "Near" analysis tool provided by ArcToolbox in ArcGIS 10.8 to calculate the shortest linear (straight-line) distance from each firm to its nearest subway station in each year of observation, based on the annually updated data on operational subways. Except for firms located in remote areas,[17] the nearest operational station may change over time, leading to year-to-year variation in the measured distance. Typically, the distance decreases when a new and closer station becomes operational.[18]

One limitation of the NTSD is that it does not have a complete panel structure, as firms appeared in the survey for various numbers of years. In addition, some firms may exhibit certain data deficiencies that render them undesirable for our study. We then take the following steps to construct the sample for our study.

First, we restrict our sample to cities that had operational subway systems by 2016. This restriction is imposed because firms in cities without subway systems would otherwise all be assigned to the control group. However, cities may differ substantially and our estimates for the effects of subway systems may capture cross-city differences. This step yields 314,997 firms

[17] Approximately 13% of firms in our sample fall into this category.

[18] To illustrate this point, consider firm X, which is observed continuously from 2011 to 2013. Before June 1, 2012, the nearest station (Station 0) was 2.7 kilometers from the firm. On June 1, 2012, a new subway line was opened, and a new station (Station 1) 1.8 kilometers away from the firm became operational. Another station (Station 2), located 3.6 kilometers away, also opened at the same time. Subsequently, on May 1, 2013, a third new station (Station 3) 1 kilometer away became operational. In this case, the firm's distance to the nearest subway station in 2011, 2012, and 2013 is recorded as 2.7 kilometers, 1.8 kilometers, and 1 kilometer, respectively.

observed during the sample period, contributing 624,676 firm-year observations. Second, we exclude firms that appear in the sample for fewer than five years. With this exercise, we build an unbalanced panel structure for our sample. Third, we drop firms with inconsistent registered addresses across years to ensure accurate spatial alignment with subway stations. Fourth, we eliminate firm-year observations that violate generally accepted accounting principles (e.g., total assets are reported as smaller than fixed assets, current assets exceed total assets, or accumulated depreciation is lower than the current-year depreciation expense). Fifth, we exclude firm-year observations with missing values for the key variables to be used in our regression analysis. The number of such observations is relatively small. Finally, we drop firms located within a 1-kilometer radius of an existing station in 2007, as these firms exhibit no within-firm variation in subway exposure during the sample period. As a result, all firms in our sample are observed in both the pre- and post-treatment periods.

After the above steps, our sample consists of 20,198 private firms located in cities with operational subway systems, contributing 116,766 firm-year observations. For the baseline analysis, we further restrict the sample to firms located within 5 kilometers of the nearest subway station. This restriction is motivated by concerns that firms located far from subway stations are more likely to operate outside core urban and satellite-city areas. As a result, their surrounding areas may have lower land prices and real estate values, making them less comparable to those near subway lines. Accordingly, the final baseline sample comprises 73,626 firm-year observations, representing 13,576 private firms. A detailed description of the sample selection procedure is provided in Appendix Table A4.

Our annual city-level socioeconomic indicators and nighttime lights data are obtained from the *China City Statistical Yearbook*, the *China Urban Construction Statistical Yearbook,* and the

National Earth System Science Data Center. These data are subsequently matched with our sample firms.

3.2. Measuring firm financing

The NTSD provides several debt-related indicators for enterprises, including accounts payable, current liabilities, long-term liabilities, long-term borrowings, and total liabilities. However, it does not provide explicit information on bank loans. Following the literature (e.g., Li et al., 2016), we proxy for bank loans by the difference (hereafter, *Liability*) between a firm's total liabilities and accounts payable, as bank loans and accounts payable are the two major forms of external financing available to firms. Based on this measure, we construct the variable *Liability_ratio*, defined as *Liability*/total assets (in percentage) at the end of the fiscal year, and use it as our main outcome variable. It captures a firm's financing capability through external channels, particularly bank borrowing.[19]

3.3. Empirical strategy

Given the staggered nature of the introduction of subway stations, we adopt a stacked difference-in-differences (DID) specification to evaluate the impact of subway station construction on private firms' financing outcomes. The DID specification requires identifying the treatment (control) group based on whether firms are (not) subject to the influence of a nearby subway station. In our baseline estimation, we define the treatment (control) group as firms located within (between) a 1-kilometer (1 and 5 kilometers) radius of a newly opened subway station built between 2007 and 2016. This is because 1 kilometer is widely considered an acceptable pedestrian

[19] As part of our robustness checks, we also employ several alternative measures of firm financing. For details, see Section 4.1.

commuting distance (Gibbons and Machin, 2005).[20] In our robustness checks, we will try other definitions of the treatment (control) groups.

Table 1 reports the distribution of distances between firms and their nearest subway stations within each city. Between 2007 and 2016, on average, 29.58% of firms were located within 1 kilometer of the nearest subway station, 16.29% between 1 and 2 kilometers, 8.20% between 2 and 3 kilometers, 5.28% between 3 and 4 kilometers, 3.97% between 4 and 5 kilometers, and 36.68% beyond 5 kilometers.

[Table 1 about here]

With the treatment (control) group defined as above, our stacked DID regression model is specified as follows:

$$Liability\_ratio_{i,t} = \alpha + \beta Treat_i \times Post_t + \eta X_{i,t} + \gamma_i + \delta_t + \epsilon_{i,t} \tag{1}$$

where the dependent variable is firms' financing outcomes (such as *Liability_ratio*); $Treat_i$ is an indicator that equals 1 (0) if firm i is located within (outside) a 1-kilometer radius of a new subway station constructed between 2007 and 2016; $Post_t$ is a time indicator that equals 1 (0) if year t falls in or after (before) the year in which the nearest station opened.[21] The parameter of interest is the coefficient of the interaction term between $Treat_i$ and $Post_t$, β, which captures the differential change in the financing outcomes of the treatment firms between the pre-event period and the post-event period, relative to the control firms.

In line with previous research (e.g., Howell, 2017; Liu and Mao, 2019; Cai and Szeidl, 2024; He et al., 2025), we control for a set of firm-level and city-level variables that may affect private

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[20] It takes 10 to 12 minutes for a typical adult to walk 1 kilometer. City plans in Beijing and Shanghai require that subway stations be within a 10-minute walk for residents living in downtown neighborhoods.
[21] Subway stations may open at different times during the calendar year, and thus data for that year may not fully capture their effects. To mitigate potential bias, we use June 30 as the cutoff date: if a station opened on or before June 30, that year is defined as the opening year; if it opened after June 30, the following year is used.

firms' financing outcomes, including firm size (*size,* the natural logarithm of firms' total assets), return on assets (*roa,* 100 times a firm's net profits divided by total assets), sales growth (*sales_growth,* 100 times the difference between firms' sales in the current and the previous fiscal years, divided by the previous year's sales), cash holdings (*cash*, 100 times firms' operating cash flow divided by total assets), administrative expenses (*admin_expense*, 100 times firms' administrative expenses divided by total assets), industry concentration (Herfindahl-Hirschman index (*hhi*) of firms' sales in each industry), tax payments (*tax*, the natural logarithm of a firm's total tax expenditure), population density (*population*, number of people living in a city per square kilometer of land area), share of the secondary industry output (*second_industrial_ratio*, 100 times the value added of the city's secondary industry divided by regional gross domestic product), and regional economic vitality (*light*, a city's nighttime lights). We also include firm and year fixed effects to control for time-invariant firm characteristics and common time trends. To avoid the influence of extreme values, all continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. Detailed definitions and summary statistics of all variables are provided in Appendix Tables A3 and A4, respectively. To account for potential heteroscedasticity and serial correlation, standard errors are clustered at the firm level throughout the regression analysis.

4. Subway stations and firm financing: empirical results

4.1. The baseline results

Table 2 reports the baseline results from our stacked DID specification, corresponding to Model (1). Column (1) presents the baseline regression without control variables, where the coefficient on the interaction term is positive and statistically significant at the 1% level. Column (2) reports the full specification, incorporating the complete set of time-varying firm- and city-level controls. The coefficient of the interaction term remains statistically significant at the 1% level. Quantitatively, the point estimate is 4.303, representing approximately 12.44 percent of the outcome mean, which is economically significant. Consistent with our expectations, being close to subway stations helps private firms' financing.

[Table 2 about here]

To check the stability of our estimates, we construct four alternative outcome variables, *Liability_A*1, *Liability_A*2, *Liability_A*3, and *Liability_A*4, and rerun Model (1). *Liability_A*1 is the natural logarithm of a firm's *Liability*. This measure captures the size effect of firm operation. *Liability_A*2 is a firm's annual borrowings divided by its total assets. It reflects a firm's ability to obtain interest-bearing debts. Higher values of *Liability_A*1 and *Liability_A*2 indicate higher financing ability for private firms. *Liability_A*3 is interest expenses divided by a firm's total debt, and *Liability_A*4 is financial expenses, also divided by a firm's total debt. These two variables capture firms' cost of financing controlling their debt levels. Therefore, their higher values indicate lower financing ability for private firms.

The results of the above four alternative outcome variables are presented in Columns (3) - (6) in Table 2. They are consistent with our baseline findings. For example, in Column (3), being close to a subway station is associated with an increase in total liability by 12.04 percent of the sample mean. The cost-saving benefit is also statistically significant. Specifically, in Column (4), the reduction in interest payments is 20.21 percent of the outcome mean. These two results complement each other and make sense. Subway stations increase the values of firms' collateral assets, which enable firms to borrow more and lower their financing costs.

Our baseline results may face several challenges, with the most serious being that the location of subway stations is not random vis-à-vis our sample firms. One concern is that subway stations tend to be built in more prosperous locations where firms already have a higher ability to obtain external financing. For example, land prices are already higher in these areas, and firms located there are typically more financially robust than firms elsewhere. These firms tend to belong to our treatment group, implying that the treatment in our research design is not random. Another related concern is the attrition of poorly-performing firms anticipating a new station to be built. Plans for subway lines are usually announced many years before they are actually built. As the opening of a new station approaches, poorly-performing firms around the station may move away to avoid high rents or cash in the rising values of their properties. In contrast, financially stronger firms stay or move in from other locations. Consequently, firms in our treatment group may exhibit stronger pre-existing performance, potentially biasing our estimation results. To assuage these concerns, we conduct a series of robustness checks in the following subsections.

4.2. Testing pre-trends

The exogeneity assumption of the DID design can be verified or rejected by testing the assumption of parallel trends, which requires that the outcome variable exhibits similar trends in the treatment and control groups in the absence of treatment. However, it is hard to directly test this assumption in most cases. As an (imperfect) alternative, researchers typically test whether there are pre-trends before the treatment (e.g., Beck et al., 2010). Our first robustness check is to perform an event study to rule out the presence of pre-trends. Prior to this, we first check whether the treatment group and control group are significantly different before a nearby station is opened. To this end, we compare the pre-treatment values (t = -1) of the control variables used in Table 2 across the two groups. The results, reported in Table A5 of the Appendix, show that they do not differ systematically between the two groups. This finding gives us confidence that firms in the treatment and control groups are not systematically different prior to treatment.

Following the literature (e.g., Beck et al., 2010; Roth, 2022; Rambachan and Roth, 2023), we estimate the following event-study specification:

$$Liability\_ratio_{i,t}=\alpha+\sum_{t=-6,\ t\neq 0}^{t=-6} \beta_t Y_t +\eta X_{i,t}+\gamma_i+\delta_t+\epsilon_{i,t} \quad (2)$$

where Y_t is an indicator of the year relative to the year when a nearby station was opened, and β_t captures the treatment effect in each year. Figure 3 provides a visual presentation of the estimation results from Model (2). Prior to the opening of a nearby subway station, there are no statistically significant differences between the treatment group and the control group.[22] In contrast, following the opening of a station, the treatment effect becomes pronounced and persists over time. These findings alleviate concerns about pre-trends and provide support for the validity of our identification strategy, suggesting that our estimates are unlikely to be contaminated by the endogenous location of subway stations.

[Figure 3 about here]

4.3. Propensity score matching

We next employ propensity score matching (PSM) to construct a more comparable treatment group and control group and re-estimate Model (1). We implement a one-to-one nearest-neighbor matching procedure without replacement. For each treated firm (i.e., a firm located within a 1-kilometer radius of an operational subway station), we identify the closest control firm (i.e., a firm located beyond the 1-kilometer radius of an operational subway station) based on propensity scores estimated in the corresponding treatment year. To ensure high-quality matching, we impose a strict

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[22] Although some studies document anticipatory effects of subway construction announcements on property prices prior to the opening of subway stations (e.g., McMillen and McDonald, 2003; Keeler and Stephens, 2023), we find no evidence of such effects in our setting. This may be attributable to construction-related negative externalities (e.g., noise, dust, and traffic congestion), the long and uncertain lags between construction and operation, and the possibility that favorable information is rapidly capitalized into asset prices at the time of announcement of the subway construction.

caliper equal to 1% of the standard deviation of the estimated propensity scores. The covariates used to estimate the propensity scores include firm size (*size*), sales growth (*sales_growth*), cash holdings (*cash*), industry concentration (*hhi*), and firm tax payments (*tax*). After matching, the final sample consists of 38,097 firm-year observations from 11,505 firms.

To assess the quality of the propensity score matching procedure, we examine the extent of overlap in the propensity score distributions between treated and control firms. Figure A4 presents the results of the common support test. As shown in Figure A4-*a*, there are noticeable discrepancies in the propensity score distributions prior to matching, suggesting an initial imbalance between the two groups. In contrast, after matching, as shown in Figure A4-*b*, the distributions converge substantially, indicating improved comparability. Although the matching procedure cannot fully eliminate endogeneity concerns (because the treatment and control groups are defined by geographical distances, which are not included in the matching process), it indeed helps improve the comparability between treated and control firms and thus enhances the credibility of our DID estimates.

Appendix Table A6 reports two sets of results from the DID estimation using the matched sample. Column (1) does not include any control variables, and Column (2) does. The magnitudes of the DID estimators have increased substantially compared to the baseline specification. Although we do not interpret these results as evidence of exogenous subway construction, the PSM-based results provide additional support for our conclusion that proximity to subway stations enhances private firms' ability to secure financing.

4.4. Alternative definitions of the treatment and control groups

We further examine whether our baseline results are sensitive to alternative definitions of the treatment and control groups. Although a 1-kilometer radius is commonly regarded as an appropriate threshold for pedestrian commuting, using this cutoff to define the treatment group may still be potentially arbitrary. We therefore redefine the treatment group as firms located within 1.5 kilometers and 2 kilometers of an operational subway station, respectively. Presumably, our estimator will become weaker once we adopt these two alternative definitions. We also vary the definition of the control group by narrowing and expanding its spatial range. Specifically, we restrict the sample to firms located within 3 kilometers, within 10 kilometers, and beyond a 1-kilometer (without an upper bound) from a newly opened subway station. In all three cases, the treatment group continues to consist of firms located within the 1-kilometer radius, while the control group includes firms outside this radius.

Table 3 reports the results. Columns (1) and (2) correspond to the two alternative definitions of the treatment group. In both cases, the DID estimates remain statistically significant, although their magnitudes and significance levels decline relative to the baseline specification. The estimate based on a 1.5-kilometer radius is larger than that based on a 2-kilometer radius, and both are smaller than the baseline estimate. This monotonic decline along the geographic gradient confirms our conjecture that the effect of subway stations attenuates when the treatment group is broadened. A similar pattern is found when the control group is redefined. Columns (3) - (5) present results using control groups defined as firms located within 1-3 kilometers, within 1-10 kilometers, and beyond 1 kilometer (without an upper bound) from a newly opened subway station, respectively. The three estimates follow a declining order, and the baseline estimate (when the control group is defined as firms located within a 1-5 kilometer radius) fits perfectly between the first estimate (when the control group is defined as firms located 1-3 kilometer radius) and the second estimate (when the control group is defined as firms located 1-10 kilometer radius), suggesting that the estimated impact is stronger when the control group is geographically closer to the treatment group.

[Table 3 about here]

These results reinforce the credibility of our baseline findings in two important ways. First, they contradict the conjecture that our baseline results stem from the tendency of subway lines to pass through more prosperous neighborhoods. If this were the case, narrowing the control group toward areas closer to stations should weaken the estimated effects, as the control firms would more resemble the treated firms and thus benefit from pre-existing prosperity. However, we observe the opposite. Second, as the control group becomes more spatially confined, firms in the control group become more comparable to those in the treatment group. Like in our PSM exercise, this increased comparability should lead to stronger estimated effects, which is precisely what is observed in our analysis.

4.5. Heterogeneous analyses

The above three sets of tests have shown that our baseline results are not likely to be subject to the issue of endogenous location of subway stations. In this and the next two subsections, we further conduct a set of heterogeneous analyses to buttress our robustness tests.

4.5.1. Sectoral analysis

First, we conduct a sectoral analysis. In China, firms in the manufacturing, construction, and transportation (MCT) sectors typically require substantial production structures and land. Therefore, the collateral channel can be important for them to obtain external financing. In contrast, service firms often rent buildings for their operations, so the collateral effect could be weaker for these firms. Figure A5 illustrates the spatial distribution of MCT firms and service firms in Beijing and Shanghai. MCT firms tend to locate in peripheral urban areas, suburban zones, and designated industrial parks, where land and factory space are more affordable for large-scale operations. In contrast, service firms rely heavily on direct access to customers, so their headquarters are often clustered in central business districts.

We split the sample into two subsamples, one comprising MCT firms and the other service firms. The first two columns of Table 4 report the results for MCT firms and service firms, respectively. In both columns, the DID estimator is positive and statistically significant, but its magnitude is substantially larger in column (1) than in column (2). This result has two implications. One is that the collateral effect is larger for MCT firms than for service firms, and the other is that the effect is more likely to be driven by subway construction itself rather than by favorable geographic locations.

[Table 4 about here]

4.5.2. The impacts of firm size

Second, we conduct a firm-size analysis to address the concern that our baseline results are driven by large firms. Intuitively, large firms are more likely to own land and buildings than small and medium-sized enterprises. Consequently, they are more likely to benefit from increases in asset values resulting from improved subway access. In addition, financial institutions may be more inclined to recognize and capitalize on subway-induced collateral appreciation when lending to larger firms, given their lower perceived risk and stronger balance sheets. A seemingly natural conjecture is that the collateral channel may work for large firms. To examine this conjecture, we split the sample into large enterprises (LEs) and small and medium-sized enterprises (SMEs).[23]

Columns (3) and (4) of Table 4 report the results for LEs and SMEs, respectively. The DID estimator is larger in Column (3) than in Column (4), but its statistical significance is lower, likely

[23] We classify firms using criteria such as number of employees, operating revenue, and total assets, with classification thresholds adjusted according to industry characteristics, following the standards of the National Bureau of Statistics of China (see www.stats.gov.cn/zs/tjws/tjbz/202301/t20230101_1903367.html).

due to the smaller number of observations for LEs. The more important result is that the DID estimator for SMEs is almost as large as our baseline results. Because firms in our whole sample are overwhelmingly SMEs, this result is not surprising.

4.5.3. State-owned enterprises as a placebo test

Finally, we conduct a placebo test using state-owned enterprises (SOEs) as the placebo group. Unlike private firms, SOEs face fewer financing constraints due to implicit or explicit government guarantees and support. Consequently, the financing behavior of SOEs should be largely insensitive to the introduction of subway stations. Accordingly, we expect subway expansion to have no significant impact on SOE financing.

To verify this prediction, we re-estimate the baseline specification reported in Columns (1) and (2) of Table 2 using the sample of SOEs. Columns (5) and (6) in Table 4 present the results. Consistent with our expectation, the introduction of subway stations has no statistically significant impact on SOE financing. This placebo test corroborates our premise that subway stations increase the financing capacity of credit-constrained firms.

5. Testing the collateral channel

The key premise of our study is that the financial accelerator effect of subway construction arises from subways' role in increasing the value of firms' collateral assets. In this section, we empirically test this premise by examining the mechanism, i.e., to show that subway stations improve firms' external financing through the collateral channel. Our empirical strategy proceeds in two steps. First, we show that subway construction increases the value of firms' collateral assets. Second, we examine whether collateral values affect firms' access to external financing.

5.1. Subway stations and the value of collateral assets

We begin by examining whether subway construction increases the value of assets that can be pledged as collateral. To this end, we focus on two types of assets that Chinese banks predominantly accept as collateral, i.e., production/operational buildings and land owned by firms. The NTSD records the net book value of a firm's production- and operational-related buildings at the end of the fiscal year. However, the NTSD does not record the market value of firms' land. To address this limitation, we rely on firms' land-use tax payments to proxy for both land ownership and land value. In China, a firm's land-use tax is assessed based on the taxable land area multiplied by locality-specific statutory rates. These statutory rates are largely determined by factors such as the quality and accessibility of infrastructure and the level of regional economic development. Thus, firms' land parcels situated near subway stations typically face higher statutory rates. Accordingly, land-use tax payments directly capture the underlying economic value of the land, because higher land-use tax payments are associated with larger or more valuable land parcels.[24]

To test whether subway stations improve the value of firms' collateral assets of production structures and land holdings, we construct two outcome variables, *building_value* and *landuse_value*, which are defined as the natural logarithm of the value of a firm's production/operational buildings and land-use tax payments during the fiscal year, respectively.[25] We then re-estimate Model (1) using these two variables as the dependent variables.

The corresponding results are reported in Columns (1) and (2) of Table 5. The results are very illuminating. Subway stations significantly increase the values of the two kinds of collateral assets. Specifically, firms located within a 1-kilometer radius of a subway station enjoy a 15.1 percent

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[24] For detailed regulatory provisions, see the Provisional Regulations of the People's Republic of China on Urban Land-Use Tax (fgk.chinatax.gov.cn/zcfgk/c100010/c5194445/content.html).

[25] In our sample, 84 subsidiaries have data on both the value of production/operational buildings and land-use tax information, yielding 388 firm-year observations.

premium in their building values over firms located 1-5 kilometers away. Although the effect on land values is much smaller — the premium is only 3.4 percent — the estimate remains highly statistically significant. One reason for this small effect is that the number of firms owning land is small.

[Table 5 about here]

One potential issue that can be raised for the above results is that many firms don't own any production structures or land, so these results may be biased. To address this issue, we employ the Heckman two-step model to re-examine the analysis.

For the first stage, we estimate a probit regression of whether firms purchase production structures (*building_purchase*) and land (*landuse_purchase*). This exercise itself is informative, as it tells us whether firms tend to purchase more production structures and land following the opening of a nearby subway station. We include all control variables from our baseline regressions. The Heckman two-step approach requires additional exogenous variables that are correlated with the likelihood of purchases, but do not directly affect the market values of the assets themselves (i.e., *building_value* and *landuse_value*). To this end, we employ three instruments for the analysis: (i) whether the firm operates in the industrial sector (*industry_dummy*, equal to 1 if a firm is an industrial firm, and 0 otherwise), (ii) firm age (*firm_age*, the natural logarithm of the number of years since a firm's initial establishment), and (iii) subsidies (*subsidies*, the natural logarithm of government subsidies in the fiscal year). Specifically, industrial firms are more likely to purchase production structures and land because leasing arrangements may lead to a hold-up problem that is not conducive to their long-term operation. Similarly, older firms with a longer operational history tend to have a longer time horizon. Additionally, firms receiving higher government subsidies possess greater financial capacity to invest in production structures and land. Meanwhile, these characteristics are unlikely to affect the market values of production structures and land, thus meeting the "exclusion restriction" assumption for valid instrumental variables.

Appendix Table A7 presents the first-stage results. Consistent with our expectation, the coefficients of the instrumental variables, *industry_dummy*, *firm_age*, and *subsidies* are all positive and highly significant. Moreover, the DID estimator remains positive and highly significant. Locating close to a subway station increases a firm's probability of purchasing production structures by 11.3 percent, and its probability of purchasing land by 3.9 percent.

In the second stage, we estimate the effects of the proximity to subway stations on collateral values while controlling for the inverse Mills ratio obtained from the first stage. Columns (3) and (4) of Table 5 present the results. The DID estimator remains significantly positive. Its magnitude slightly declines for production structures, but slightly increases for land compared to the corresponding results in Columns (1) and (2), respectively.[26]

5.2. Collateral assets and external financing

Next, we examine whether collateral assets mediate the effect of subway stations on firm financing. As a first step, we regress *Liability_ratio* on *building_value* and *landuse_value*, respectively. The results are presented in Table A8 in the Appendix. Both collateral assets are positively and significantly associated with firms' external financing. This finding is consistent with the collateral mechanism proposed by this paper. However, because *building_value* and *landuse*_value are themselves outcome variables influenced by subway construction, these regressions are intended to be suggestive rather than to establish any causal relationship. Thus, we

[26] The coefficients on the inverse Mills ratio in Columns (3) and (4) are statistically significant, suggesting that the unobserved factors driving firms' decisions to purchase production structures and land are correlated with the value of these assets.

conduct the following rigorous analysis to establish a causal relationship between collateral assets and firm financing.

To do so, we partition our sample into two subsamples based on whether a firm owned production structures and/or land in the first year the firm appears in our sample. We then rerun Model (1) on the partitioned samples, respectively, starting from the second year onward. Because we have eliminated firms with a nearby station before they appeared in the time windown of our sample, the ownership of buildings and land proceeded subway construction and was therefore exogenous. Therefore, the contrast between the two subsamples will establish a causal role for collateral assets in mediating subway stations' impacts on firm financing.

Table 6 presents the results. Columns (1) and (2) compare firms with buildings or land with those without either kind of assets. The contrast is clear: the DID estimator is significantly positive for the first group of firms and insignificant for the second group. That is, subway stations only improve firms' ability to obtain external financing when they have collateral assets (in this case, buildings or land). The effect is slightly larger than the one we found in our baseline regressions, thus buttressing our main results.

[Table 6 about here]

We additionally conduct a continuous-variable DID estimation to check the robustness of the above result. To do so, we employ the following specification to conduct the estimation:

$$\begin{aligned} Liability\_ratio_{i,t} &= \alpha+\beta_1 Treat_i\times Post_t\times building\_value\ (landuse\_value)_{i,t}+\beta_2 Treat_i\times Post_t \\ &\quad +\beta_3 building\_value\ (landuse\_value)_{i,t}+\eta X_{i,t}+\gamma_i+\delta_t+\epsilon_{i,t} \qquad (3) \end{aligned}$$

The coefficient of interest, β_1, on the triple interaction term measures the net effect of the differences in financing between firms with collateral assets of production structures or land holdings and firms without. As shown in Columns (3) and (4) of Table 6, β_1 is statistically significant and has the expected sign. The point estimates indicate that a one-percent increase in the value of production structures leads to a 0.609 percentage point increase in firm financing. More strikingly, a one-percent increase in land value leads to a 2.435 percentage point increase in firm financing. These effects are economically substantial.

Collectively, the above two sets of results provide compelling evidence that collateral assets play a crucial mediating role through which subway stations enhance firms' access to external financing. This completes our proof that subway stations increase firm financing through the collateral channel.

6. Conclusion

We document a novel collateral channel through which government infrastructure investment positively affects private-sector financing. Our empirical analysis exploits China's large-scale subway expansion and a purposefully built geo-financial dataset linking taxed private firms to their nearest subway stations between 2007 and 2016. In contrast to the well-documented crowding-out effect that is typically associated with government spending, we provide causal evidence that proximity to subway stations increases private firms' external financing. We refer to this as the "financial-accelerator effect" of infrastructure investment. Our mechanism analysis further reveals that the opening of a nearby subway station raises the collateral values of firms' production structures and land holdings, and the financial-accelerator effect works through the collateral channel.

Our findings underscore the complexity of government investment. Finding a channel for government investment to affect firm financing, we enhance the understanding of the dynamic interactions between fiscal and monetary policies. Resonating with the empirical research of the financial accelerator literature,[27] The financial accelerator effect that we have found for subway construction indicates that governments' fiscal expansion/contraction can cause overshooting in the economy through the credit market. When monetary expansion is needed to boost domestic aggregate demand, complementary fiscal expansion will lend a hand so monetary expansion does not need to be radical. But when monetary tightening happens, fiscal austerity will amplify credit contraction. Studies of China's 2017-2019 deleveraging campaign have confirmed this assertion (e.g., Hu et al., 2025). Realizing this, the monetary authorities should refrain from conducting drastic credit expansion or contraction. This is particularly important for countries with a relatively shallow financial market that is incapable of absorbing large monetary shocks.

[27] There is a rich empirical literature on the financial accelerator in the context of government policy interventions (Gertler et al., 2007), real estate markets (Mertens and Ravn, 2011), capital flows (Jeanne and Korinek, 2010), risk premia (Carrillo, 2021), and financial leasing (Li and Yu, 2023).

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Table 1: Distribution of firms by distance to the nearest subway station

Subway_firm_distance	Percentage
≤1km	29.58%
1-2km	16.29%
2-3km	8.20%
3-4km	5.28%
4-5km	3.97%
>5km	36.68%

Notes: This table reports the distribution of sample firms based on their distance to the nearest operational subway station. The variable *Subway_firm_distance* measures the straight-line (Euclidean) distance between each firm's registered location and the closest subway station within the same city. Distances are categorized into six groups: ≤1 km, 1-2 km, 2-3 km, 3-4 km, 4-5 km, and >5 km. The percentage column indicates the proportion of firms falling within each distance range.

Table 2: Subway stations and private firm financing

Variables	(1) Dependent variable = $Liability\_ratio_t$	(2) Dependent variable = $Liability\_ratio_t$	(3) Dependent variable = $Liability\_A1_t$	(4) Dependent variable = $Liability\_A2_t$	(5) Dependent variable = $Liability\_A3_t$	(6) Dependent variable = $Liability\_A4_t$
Treat×Post	4.529***	4.303***	1.075**	19.685***	-0.264**	-1.634***
	(2.815)	(2.719)	(2.089)	(4.010)	(-2.191)	(-3.780)
$size_t$		2.636***	0.414***	-4.099***	0.047*	-0.317***
		(8.753)	(29.330)	(-2.663)	(1.847)	(-4.641)
roa_t		-0.006	-0.002***	-0.092***	0.002**	0.020***
		(-0.338)	(-4.236)	(-3.329)	(2.221)	(7.330)
$sales\_growth_t$		0.000	-0.000	-0.009***	-0.000	0.000***
		(0.107)	(-0.103)	(-15.635)	(-0.083)	(4.195)
$cash_t$		-0.001	-0.003***	0.004	0.002***	-0.012***
		(-0.141)	(-14.533)	(0.356)	(4.127)	(-10.512)
$admin\_expense_t$		-0.022	-0.009***	-0.072**	0.009***	0.023***
		(-0.944)	(-16.942)	(-2.088)	(6.602)	(5.423)
hhi_t		-0.007	0.001	0.279***	0.006***	0.006
		(-0.288)	(1.107)	(2.701)	(2.981)	(1.012)
tax_t		0.474***	0.054***	3.499***	0.029***	-0.308***
		(4.257)	(15.374)	(8.683)	(3.056)	(-9.566)
$population_t$		5.382***	0.217***	-48.203***	-0.433***	-3.466***
		(5.592)	(7.381)	(-9.542)	(-3.765)	(-14.957)
$second\_industrial\_ratio_t$		-0.585	0.155***	39.505***	0.515***	0.784**
		(-0.486)	(4.929)	(6.735)	(4.615)	(2.481)
$light_t$		-0.828***	-0.027***	1.103***	-0.033***	-0.055
		(-4.935)	(-6.141)	(3.374)	(-2.946)	(-1.146)
Constant	32.463***	-8.318	3.825***	288.990***	3.521***	35.479***
	(43.093)	(-1.015)	(14.047)	(8.764)	(4.156)	(17.937)
Firm FEs	Included	Included	Included	Included	Included	Included
Year FEs	Included	Included	Included	Included	Included	Included
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,626	73,626	73,626	73,626	73,626	73,626
Adj. R2	0.254	0.256	0.635	0.165	0.215	0.259
Mean of dep. var.	34.583	34.583	8.932	38.039	1.306	6.220

Notes: This table reports the OLS regression results for the association between subway station construction and private firms' financing. Columns (1)-(2) report the estimation results using *Liability_ratio* as the measure of private firms' financing. Columns (3)-(6) report the estimation results using *Liability_A*1, *Liability_A*2, *Liability_A*3, and *Liability_A*4 as the alternative measures of private firms' financing, respectively. The sample period ranges from 2007 to 2016. The treatment indicator variable, *Treat*, equals 1 (0) if a firm is located within (beyond) a 1-kilometer radius of a new subway station constructed between 2007 and 2016. *Post* is a time indicator which equals 1 (0) if the year is in the post- (pre-) event period. Year dummies and firm dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Alternative treatment groups and control groups

	Dependent variable = *Liability_ratio*$_t$				
	(1)	(2)	(3)	(4)	(5)
Variables	Treatment group <= 1.5km	Treatment group <= 2km	1km < Control group <= 3km	1km < Control group <= 10km	1km < Control group
Treat1×Post	3.519**				
	(2.154)				
Treat2×Post		2.959*			
		(1.854)			
Treat3×Post			4.554***		
			(2.580)		
Treat4×Post				3.914**	
				(2.535)	
Treat5×Post					3.051**
					(2.104)
Constant	-8.641	-8.469	0.020	-4.861	3.102
	(-1.053)	(-1.030)	(0.002)	(-0.660)	(0.540)
Controls	Included	Included	Included	Included	Included
Firm FEs	Included	Included	Included	Included	Included
Year FEs	Included	Included	Included	Included	Included
Cluster by firm	Yes	Yes	Yes	Yes	Yes
Observations	73,626	73,626	62,761	86,948	116,766
Adj. R2	0.256	0.256	0.262	0.240	0.243
Mean of dep. var.	34.583	34.583	34.665	34.763	35.206

Notes: This table reports the estimation results using alternative definitions of the treatment and control groups. Columns (1)-(2) report the estimation results using alternative treatment groups, and Columns (3)-(5) report the results of alternative control groups. The sample period ranges from 2007 to 2016. Year dummies and firm dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Heterogeneity analyses

	Dependent variable = *Liability_ratio$_t$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	MCT firms	Service firms	LEs	SMEs	SOEs	SOEs
Treat×Post	16.359***	3.570***	5.678*	4.371***	2.986	2.867
	(3.367)	(3.245)	(1.882)	(2.647)	(1.235)	(1.191)
Constant	-44.019	44.590***	32.243	-12.163	37.970***	2.865
	(-1.190)	(3.424)	(0.907)	(-1.431)	(27.168)	(0.200)
Controls	Included	Included	Included	Included	Excluded	Included
Firm FEs	Included	Included	Included	Included	Included	Included
Year FEs	Included	Included	Included	Included	Included	Included
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,821	38,721	3,460	69,621	22,429	22,429
Adj. R2	0.279	0.294	0.615	0.248	0.295	0.301
Mean of dep. var.	39.978	34.241	47.051	33.902	39.696	39.696

Notes: This table reports regression results of heterogeneous analyses. Column (1) reports the estimation results for MCT firms. Column (2) reports the estimation results for service firms. Column (3) reports the estimation results for LEs. Column (4) reports the estimation results for SMEs. Column (5) reports the estimation results based on a sample of SOEs without control variables. Column (6) reports the estimation results based on a sample of SOEs that includes *Treat×Post* and the control variables. The sample period ranges from 2007 to 2016. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Subway stations and firms' collateral assets

Variables	OLS regression		Heckman two-stage regression	
	(1)	(2)	(3)	(4)
	Dependent variable = *building_value*$_t$	Dependent variable = *landuse_value*$_t$	Dependent variable = *building_value*$_t$	Dependent variable = *landuse_value*$_t$
Treat×Post	0.151***	0.034**	0.129***	0.036**
	(3.179)	(2.113)	(2.722)	(2.239)
Constant	-0.210	-0.925***	0.178	-0.682***
	(-0.559)	(-7.815)	(0.470)	(-5.636)
Controls	Included	Included	Included	Included
Firm FEs	Included	Included	Included	Included
Year FEs	Included	Included	Included	Included
Cluster by firm	Yes	Yes	Yes	Yes
Observations	73,626	73,626	73,605	73,605
Adj. R2	0.760	0.821	0.761	0.823
Mean of dep. var.	3.551	0.783	3.550	0.783

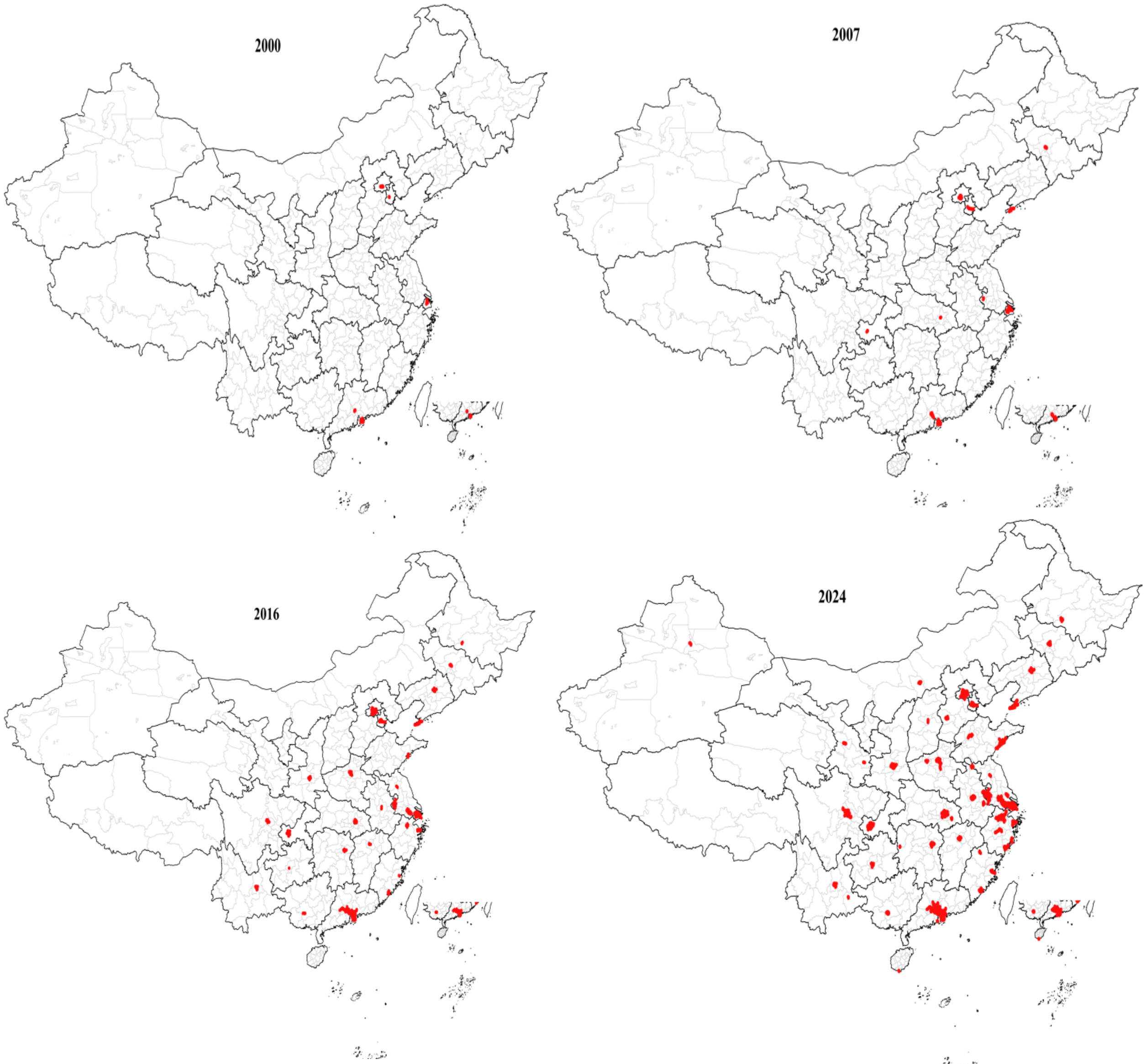
Notes: This table reports the estimation results for the association between subway station construction and firms' collateral assets. Columns (1)-(2) present the OLS regression results of the value of production structures (*building_value*) and land (*landuse_value*) on subway station construction (*Treat×Post*), respectively. Columns (3)-(4) present the Heckman regression results of the value of production structures (*building_value*) and land (*landuse_value*) on subway station construction (*Treat×Post*), respectively. The sample period ranges from 2007 to 2016. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. All regressions include year and firm dummies, although their coefficients are not reported for brevity. t-statistics are computed using robust standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: The mediating effects of firms' collateral assets

	Dependent variable = *Liability_ratio*$_t$			
	(1)	(2)	(3)	(4)
Variables	*collateral_value* > 0	*collateral_value* = 0	Full sample	Full sample
Treat×Post×building_value			0.609***	
			(2.635)	
Treat×Post×landuse_value				2.435***
				(3.110)
Treat×Post	6.696**	0.523	2.014	2.119
	(2.128)	(0.406)	(0.914)	(0.314)
building_value			4.287***	
			(26.194)	
landuse_value				5.187***
				(6.543)
Constant	-17.160	50.385***	-10.690	-5.485
	(-1.075)	(5.287)	(-1.154)	(-0.583)
Controls	Included	Included	Included	Included
Firm FEs	Included	Included	Included	Included
Year FEs	Included	Included	Included	Included
Cluster by firm	Yes	Yes	Yes	Yes
Observations	33,845	29,696	62,423	62,423
Adj. R2	0.531	0.160	0.265	0.253
Mean of dep. var.	36.494	36.847	34.693	34.693

Notes: This table reports the mediating effects of firms' collateral asset ownership on the causal relationship between subway station construction and private firms' financing. Columns (1) and (2) present the results of the baseline regressions estimated for subsamples of firms that own production structures or land (*collateral_value* > 0) and those without production structures or land (*collateral_value* = 0). Columns (3) and (4) report the mediating effects of firms' collateral asset values, captured by the interaction terms between *Treat×Post* and the value of firms' production structures (*building_value*) and land holdings (*landuse_value*), respectively. The sample spans from the second year a firm appears onwards. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. All regressions include year and firm fixed effects, although their coefficients are not reported for brevity. t-statistics are calculated using robust standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

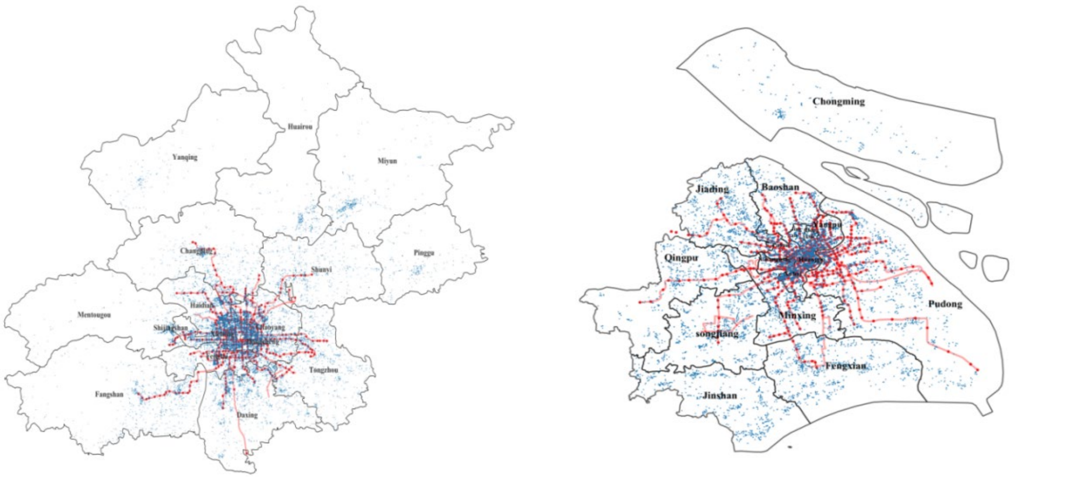
Figure 1: The growth of subway networks from 2000 to 2024



Notes: This figure displays the expansion of China's subway networks from 2000 to 2024. The red lines represent subway routes, and the red dots indicate subway stations. Sources: *Statistical Yearbooks of Chinese Cities* and the official website of the Association of Metros (www.camet.org.cn/).

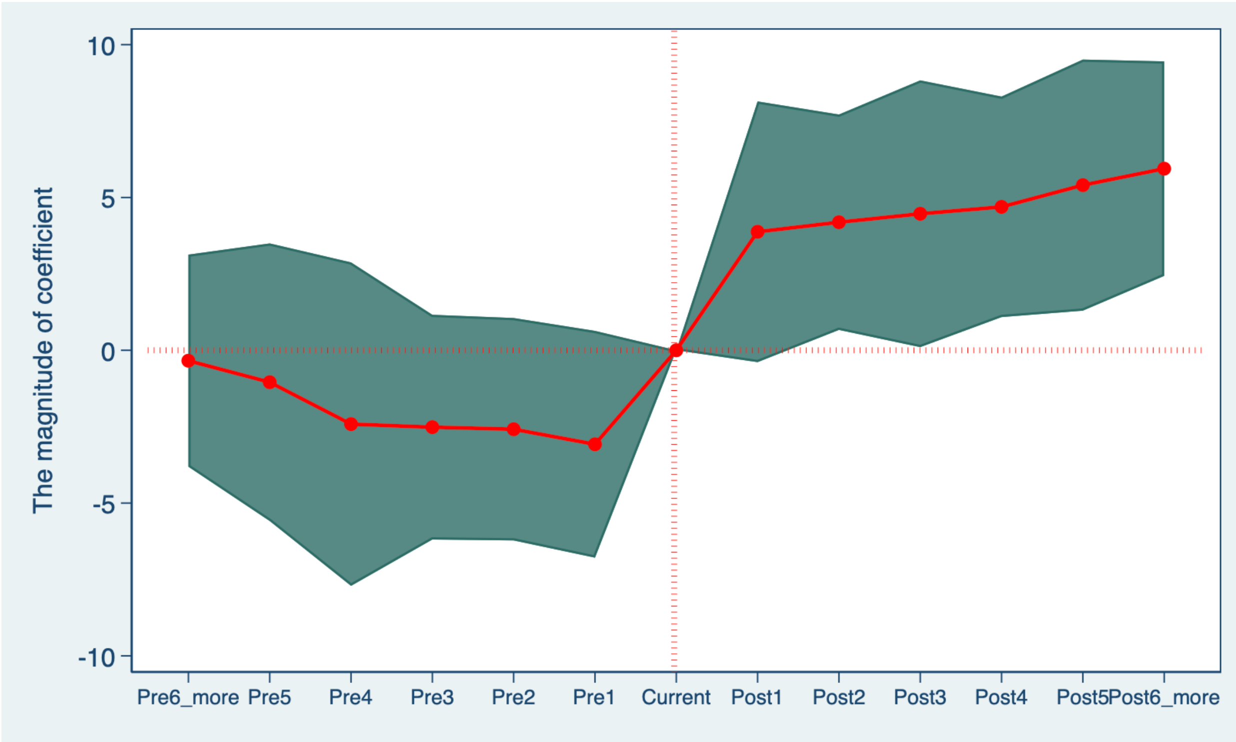
Figure 2: Subway lines and the distribution of private firms in Beijing and Shanghai

(*a*) Beijing (*b*) Shanghai



Notes: This figure presents the geographic distribution of subway systems and private firms in Beijing and Shanghai between 2007 and 2016. The subway lines are for 2016, and the distribution of firms represents the average distribution over the period 2007-2016. The red lines represent subway routes, red dots indicate subway stations, and blue dots denote the locations of private firms. Sources: firm-level data are obtained from the National Tax Survey Database (NTSD), subway information comes from *Statistical Yearbooks of Chinese Cities* and the official website of the Association of Metros (www.camet.org.cn/).

Figure 3: Results of the event study



Notes: This figure presents the coefficient estimates and their 95% confidence intervals (shaded areas) based on Model (2). The horizontal axis denotes the year dummies, and the vertical axis represents the corresponding estimates. The year of the event (the opening of a nearby subway station) is labeled by *current*. Six years before the event (years before the sixth year are compressed to the sixth year dummy *Pre*6*_more*) and six years after the event (years after the sixth year are compressed to the sixth year dummy *Post*6*_more*) are considered. Standard errors of the coefficients are adjusted for heteroskedasticity and clustered at the firm level. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed definitions are provided in Appendix Table A3.

Appendix

Table A1: Details of operation of subway Lines

year	Lines
1971	Beijing Line 1, Beijing Line 2
1976	Tianjin Line 1
1993	Shanghai Line 1
1997	Guangzhou Line 1
1999	Shanghai Line 2
2000	Shanghai Line 3
2002	Beijing Line 13, Guangzhou Line 2, Guangzhou Line 8, Changchun Line 3
2003	Shanghai Line 5, Dalian Line 3, Dalian Line 3 Jiuli Branch Line
2004	Tianjin Line 9, Wuhan Line 1, Shenzhen Line 1, Shenzhen Line 4, Chongqing Line 2
2005	Shanghai Line 4, Nanjing Line 10, Nanjing Line 1, Guangzhou Line 3, Guangzhou Line 4
2006	Guangzhou Line 10
2007	Shanghai Line 6, Shanghai Line 8, Shanghai Line 9, Beijing Line 5
2008	Beijing Line 10, Beijing Line 8, Beijing Capital Airport Line
2009	Shanghai Line 11, Shanghai Line 7, Beijing Line 4, Guangzhou Line 5
2010	Shanghai Line 10, Shanghai Expo Line, Beijing Line 15, Beijing Yizhuang Line, Beijing Daxing Line, Beijing Fangshan Line, Beijing Changping Line, Nanjing Line 2, Chengdu Line 1, Shenyang Line 1, Shenzhen Line 2, Shenzhen Line 3
2011	Beijing Line 9, Shenyang Line 2, Shenzhen Line 5, Xi'an Line 2, Chongqing Line 3
2012	Shanghai Line 13, Beijing Line 6, Tianjin Line 2, Tianjin Line 3, Chengdu Line 2, Kunming Line 6, Hangzhou Line 1, Hangzhou Line 9, Wuhan Line 2, Suzhou Line 1, Chongqing Line 1, Chongqing Line 6, Changchun Line 4
2013	Shanghai Line 12, Shanghai Line 16, Beijing Line 14, Harbin Line 1, Guangzhou Line 6, Kunming Line 1, Kunming Line 2, Wuhan Line 4, Suzhou Line 2, Xi'an Line 1, Zhengzhou Line 1
2014	Beijing Line 7, Nanjing S1 Line, Nanjing S8 Line, Dalian Line 12, Ningbo Line 1, Wuxi Line 1, Wuxi Line 2, Hangzhou Line 2, Changsha Line 2
2015	Nanjing Line 3, Nanchang Line 1, Dalian Line 1, Dalian Line 2, Ningbo Line 2, Chengdu Line 1 Branch, Chengdu Line 4, Hangzhou Line 4, Wuhan Line 3, Qingdao Line 3
2016	Dongguan Line 2, Beijing Line 16, Nanning Line 1, Hefei Line 1, Tianjin Line 6, Guangzhou Line 7, Chengdu Line 3, Wuhan Line 6, Shenzhen Line 11, Shenzhen Line 7, Shenzhen Line 9, Fuzhou Line 1, Xi'an Line 3, Zhengzhou Line 2, Changsha Line 1, Qingdao Line 2
2017	Shanghai Line 17, Beijing Yan Fang Line, Nanjing Line 4, Nanjing S3 Line, Nanjing S9 Line, Nanning Line 2, Nanchang Line 2, Xiamen Line 1, Hefei Line 2, Harbin Line 3, Guangzhou Line 13, Guangzhou Line 14, Guangzhou Line 9, Chengdu Line 10, Chengdu Line 7, Kunming Line 3, Kunming Line 9, Wuhan Line 21, Wuhan Line 8, Wuhan Yangluo Line, Shijiazhuang Line 1, Shijiazhuang Line 3, Suzhou Line 4, Suzhou Line 7, Guiyang Line 1, Zhengzhou Urban-Rural Line, Chongqing Line 10, Chongqing Line 5, Changchun Line 1
2018	Urumqi Line 1, Nanjing S7 Line, Tianjin Line 5, Guangzhou Line 21, Wuhan Line 11, Wuhan Line 7, Xi'an Line 4, Chongqing Line 4, Chongqing Loop Line, Changchun Line 2, Changchun Line 8
2019	Lanzhou Line 1, Beijing Daxing Airport Line, Nanning Line 3, Xiamen Line 2, Hefei Line 3, Hohhot Line 1, Ningbo Line 3, Changzhou Line 1, Xuzhou Line 1, Chengdu Line 5, Hangzhou Line 5, Wuhan Line 4 (Caidian Section), Shenyang Line 9, Jinan Line 1, Jinan Line 3, Wenzhou S1 Line, Fuzhou Line 2, Suzhou Line 3, Xi'an Line 14, Zhengzhou Line 14, Zhengzhou Line 5, Changsha Line 4
2020	Shanghai Line 18, Nanning Line 4, Nanchang Line 3, Hefei Line 5, Hohhot Line 2, Taiyuan Line 2, Ningbo Line 4, Xuzhou Line 2, Chengdu Line 17, Chengdu Line 18, Chengdu Line 19, Chengdu Line 6, Chengdu Line 8, Chengdu Line 9, Wuxi Line 3, Kunming Line 4, Hangzhou Line 16, Hangzhou Line 6, Hangzhou Line 7, Shenyang Line 10, Shenzhen Line 10, Shenzhen Line 6, Shenzhen Line 8, Shijiazhuang Line 2, Shaoxing Line 1, Xi'an Line 5, Xi'an Line 6, Xi'an Line 9, Zhengzhou Line 3, Zhengzhou Line 4, Chongqing Line 6 Guobo Line, Changsha Line 3, Changsha Line 5, Qingdao Line 1, Qingdao Line 7 (current Line 1), Qingdao Line 8
2021	Shanghai Line 14, Shanghai Line 15, Foshan Line 2, Beijing Line 11, Beijing Line 17, Beijing Line 19, Beijing Batong Line, Nanjing S6 Line, Nanning Line 5, Nanchang Line 4, Xiamen Line 3, Hefei Line 4, Harbin Line 2, Dalian Line 13, Tianjin Line 4, Tianjin Line 8, Ningbo Line 5, Changzhou Line 2, Guangzhou Line 18, Xuzhou Line 3, Wuxi Line 4, Hangzhou Line 8, Wuhan Line 16, Wuhan Line 5, Luoyang Line 1, Luoyang Line 2, Jinan Line 2, Shenzhen Line 20, Wuhu Line 1, Wuhu Line 2, Suzhou Line 5, Guiyang Line 2
2022	Foshan Line 3, Nanjing Line 7, Nantong Line 1, Tianjin Line 10, Guangzhou Line 22, Kunming Line 5, Hangzhou Line 10, Hangzhou Line 19, Hangzhou Line 3, Hangzhou Line 3 Branch, Shenzhen Line 12, Shenzhen Line 14, Shenzhen Line 16, Shenzhen Line 6 Branch, Fuzhou Line 5, Fuzhou Line 6, Zhengzhou Line 6, Chongqing Line 9, Changsha Line 6, Qingdao Line 4
2023	Lanzhou Line 2, Nantong Line 2, Dalian Line 5, Tianjin Line 11, Wuhan Line 19, Shenyang Line 4, Wenzhou S2 Line, Fuzhou Line 4, Shaoxing Line 2, Suzhou Line 11, Xi'an Line 16, Guiyang Line 3, Zhengzhou Line 10, Zhengzhou Line 12, Zhengzhou Zhengxun Line, Chongqing Line 18, Chongqing Line 5/North Section, Chongqing Line 5/Da Shi Section, Changsha West Loop Line
2024	Nanjing Line 5, Guangzhou Line 28, Wuxi S1 Line, Shaoxing Line 1 Branch, Changchun Line 6, Qingdao Line 6

Table A2: Sample selection

Sample selection procedure	No. of observations	No. of firms
Observations of the population of private firms for the period 2007-2016.	624,676	314,997
Less: observations of firms with less than five years of continuous existence.	497,286	293,326
Less: observations of firms with inconsistent registration locations.	8,543	1,431
Less: observations of firms that do not comply with generally accepted accounting principles.	2,081	42
Observations for the regression include firms located near a newly opened subway station.	116,766	20,198
Observations for the main regression include firms located within 5 kilometers of a newly opened subway station.	73,626	13,576

Table A3: Summary of variable definitions

Variables	Definitions
Liability_ratio	100 times the difference between total debt and accounts payable, divided by total assets of the firm at the end of a fiscal year.
*Liability_A*1	The natural logarithm of the difference between total debt and accounts payable of the firm at the end of a fiscal year.
*Liability_A*2	100 times the average borrowing, divided by the total assets of the firm at the end of a fiscal year.
*Liability_A*3	100 times the interest expenses, divided by the total debt of the firm at the end of a fiscal year.
*Liability_A*4	100 times the financial expenses, divided by the total debt of the firm at the end of a fiscal year.
Treat	1 (0) for a treatment (control) firm. Treatment (control) firms are defined as those located within (outside) a 1-kilometer radius of a newly opened subway station constructed in 2007-2016, when restricting firms to within a 5-kilometer radius of the subway station.
*Treat*1	1 (0) for a treatment (control) firm. Treatment (control) firms are defined as those located within (outside) 1.5-kilometer radius of a newly opened subway station constructed in 2007-2016, when restricting firms to within a 5-kilometer radius of the subway station.
*Treat*2	1 (0) for a treatment (control) firm. Treatment (control) firms are defined as those located within (outside) 2-kilometer radius of a newly opened subway station constructed in 2007-2016, when restricting firms to within a 5-kilometer radius of the subway station.
*Treat*3	1 (0) for a treatment (control) firm. Treatment (control) firms are defined as those located within (outside) 1-kilometer radius of a newly opened subway station constructed in 2007-2016, when restricting firms to within 3-kilometer radius of the subway station.
*Treat*4	1 (0) for a treatment (control) firm. Treatment (control) firms are defined as those located within (outside) 1-kilometer radius of a newly opened subway station constructed in 2007-2016, when restricting firms to within 10 kilometers of the subway station.
*Treat*5	1 (0) for a treatment (control) firm. Treatment firms are defined as those located within (outside) a 1 kilometer radius of an operational subway station opened in 2007-2016, without imposing any restriction on firms' distance to the nearest subway station.
Post	1 (0) if the year is in the post- (pre-) event period. i.e., the year *t* falls in or after (before) the year in which the station opened between January and June, or the year *t* is the year after (in or before) the year in which the station opened between July and December.
building_value	The natural logarithm of net book value of production- and operational-related buildings of a firm for a fiscal year.
landuse_value	The natural logarithm of land use tax expenses of a firm during the fiscal year.
collateral_value	The natural logarithm of the sum of the net book value of a firm's production- and operational-related buildings and its land-use value (proxied by land-use tax expenses) of a firm for a fiscal year.
building_purchase	1 (0) if a firm does (not) purchase a production structure during the fiscal year.
landuse_purchase	1 (0) if a firm does (not) purchase land-use rights during the fiscal year.
size	The natural logarithm of total assets of a firm for a fiscal year.
roa	100 times the net profits, divided by the total assets of a firm at the end of a fiscal year.
sales_growth	100 times the difference between the sales for the current fiscal year and the sales for the previous year, divided by the sales in the prior year.
cash	100 times the operating cash flows, divided by the total assets of a firm for a fiscal year.
admin_expense	100 times the administration expenses, divided by the total assets of the firm for the fiscal year.
hhi	The Herfindahl-Hirschman Index computed on firms' sales for each industry in a fiscal year.
tax	The natural logarithm of the total tax expenditure of a firm for a fiscal year.
population	The number of people living in a city per square kilometer of land area in a given fiscal year.
second_industrial_ratio	100 times the secondary industry (including manufacturing, construction, and mining), divided by total regional gross domestic product (GDP) for a fiscal year.
light	The city-level nighttime light data are obtained from the National Earth System Science Data Center.
industry_dummy	1 (0) if a firm belong (does not belong) to an industry sector.

firm_age	The natural logarithm of the number of years since a firm's initial establishment.
subsidies	The natural logarithm of governmental subsidies granted to a firm for a fiscal year.

Table A4: Summary statistics of variables

Variables	N	Mean	Min.	10%	25%	50%	75%	90%	Max.	Std. Dev.
Panel A: Dependent variables										
Liability ratio (%)	73,626	34.583	-820.346	0.000	7.344	32.255	63.111	86.301	330.547	67.434
*Liability_A*1 (ln)	73,626	8.932	0.000	6.240	8.027	9.199	10.444	11.672	15.993	2.655
*Liability_A*2 (ln)	73,626	38.039	0.000	0.000	0.000	0.000	6.680	51.912	3009.607	210.518
*Liability_A*3 (%)	73,626	1.306	-10.917	-0.555	-0.035	0.025	1.341	4.170	38.422	5.197
*Liability_A*4 (%)	73,626	6.220	0.000	0.000	0.000	0.022	2.814	11.613	123.521	19.450
Panel B: Firm characteristic										
Treat	73,626	0.468	0.000	0.000	0.000	0.000	1.000	1.000	1.000	0.499
*Treat*1	73,626	0.602	0.000	0.000	0.000	1.000	1.000	1.000	1.000	0.489
*Treat*2	73,626	0.726	0.000	0.000	0.000	1.000	1.000	1.000	1.000	0.446
*Treat*3	62,760	0.548	0.000	0.000	0.000	1.000	1.000	1.000	1.000	0.498
*Treat*4	86,947	0.383	0.000	0.000	0.000	0.000	1.000	1.000	1.000	0.486
*Treat*5	116,765	0.180	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.384
Panel C: mediator variables										
building_value (ln)	73,626	3.551	0.000	0.000	0.000	5.950	6.915	7.751	10.662	3.589
land_use_tax (ln)	73,626	0.783	0.000	0.000	0.000	0.000	0.780	3.106	6.057	1.238
building_purchase	73,626	0.458	0.000	0.000	0.000	0.000	1.000	1.000	1.000	0.498
landuse_purchase	73,626	0.134	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.340
collateral_value (ln)	73,626	4.192	0.000	0.000	0.000	5.967	7.435	10.189	10.675	4.028
Panel D: Control variables										
size (ln)	73,626	9.460	0.000	7.097	8.251	9.463	10.759	11.944	14.196	2.004
roa (%)	73,626	3.522	-150.833	-6.231	-0.183	1.040	5.250	15.667	303.741	23.525
sales_growth (%)	73,626	505.007	-99.945	-44.569	-12.140	19.142	112.278	1804.217	3897.105	255.350
cash (%)	73,626	14.044	-118.020	-12.332	0.000	0.000	9.661	35.017	822.997	63.900
admin_expense (%)	73,626	19.715	0.000	1.104	3.783	9.529	21.464	44.819	396.761	33.034
hhi (%)	73,626	14.044	-118.020	-12.332	0.000	0.000	9.661	35.017	822.997	11.802
tax (%)	73,626	3.755	0.000	0.000	0.000	0.000	8.465	8.552	11.062	4.182
population	73,626	7.214	0.000	6.152	6.343	7.199	8.263	8.558	8.865	1.715
second_industrial_ratio (%)	73,626	2.198	0.030	0.070	0.530	0.820	3.060	6.690	11.700	2.599
light	73,626	27.605	1.556	7.722	13.505	27.098	43.429	48.239	54.017	15.432
industry_dummy	73,626	0.299	0.000	0.000	0.000	0.000	1.000	1.000	0.299	0.000
subsidies (ln)	73,626	2.128	0.000	0.000	0.000	0.000	4.516	5.902	13.846	2.603
firm_age (ln)	73,626	2.425	1.204	2.493	2.590	2.799	3.021	3.260	3.694	0.336

Notes: This table reports the descriptive statistics of all variables used in the multivariate tests of the association between the subway station construction and private firms' financing. Continuous variables are winsorized at the 1st and 99th percentiles points, with detailed definitions provided in Appendix Table A3. Observations that have missing values in any of the regressors are excluded from the sample used for the multivariate tests.

Table A5: Tests of between-group differences

Variables	(1) Group	(2) Mean	(3) Difference in means	(4) t-statistic	(5) p-value > 0.1?
*pre*1_*size*	Treatment	9.639	0.098	0.372	Yes
	Control	9.737			
*pre*1_*roa*	Treatment	1.820	0.642	1.137	Yes
	Control	2.463			
*pre*1_*sales_growth*	Treatment	412.146	29.336	0.205	Yes
	Control	441.482			
*pre*1_*cash*	Treatment	12.727	-1.906	-0.960	Yes
	Control	10.821			
*pre*1_*admin_expense*	Treatment	20.834	-0.989	-0.910	Yes
	Control	19.844			
*pre*1_*hhi*	Treatment	6.678	-0.434	-1.245	Yes
	Control	6.244			
*pre*1_*tax*	Treatment	2.735	0.134	1.007	Yes
	Control	2.869			

This table reports differences in pre-treatment economic performance between the treatment and control groups. The treatment indicator, *Treat*, equals 1 (0) if a firm is located within (outside) a 1-kilometer radius of a newly opened subway station built between 2007 and 2016. We include seven firm-level variables — *size*, *roa*, *sales_growth*, *cash*, *admin_expense*, *hhi*, and *tax*. Column (2) reports mean values for the treatment and control groups in the pre-treatment period (*pre*1). Column (3) reports the difference in means (treatment minus control). Column (4) reports the corresponding t-statistics. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3.

Table A6: PSM results

Variables	(1) Dependent variable = *Liability_ratio*$_t$	(2) Dependent variable = *Liability_ratio*$_t$
Treat×Post	6.814***	6.316***
	(2.879)	(2.729)
Constant	31.037***	842.291***
	(25.769)	(5.350)
Controls	Excluded	Included
Firm FE	Included	Included
Year FE	Included	Included
Cluster by firm	Yes	Yes
Observations	38,097	38,097
Adj. R2	0.270	0.274
Mean of dep. var.	40.605	40.611

Notes: This table reports the DID results for the PSM sample. Column (1) reports the results of the univariate regression that includes Treat×Post and excludes the control variables. Column (2) reports the results of the multivariate regression that includes *Treat*×*Post* and the control variables. The treatment indicator variable, *Treat*, equals 1 (0) if a firm is located within (outside) 1-kilometer radius of a newly opened subway station in year t. *Post* is the time indicator which equals 1 (0) if the year is in the post- (pre-) event period. The sample period ranges from 2007 to 2016. Year dummies and firm dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7: First-stage results of the Heckman two-stage estimation

Variables	(1) Dependent variable = *building_purchase*$_t$	(2) Dependent variable = *landuse_purchase*$_t$
Treat×Post	0.113***	0.039***
	(10.814)	(2.943)
industry_dummy	0.101***	0.237***
	(8.535)	(14.633)
firm_age	0.051***	0.090***
	(43.580)	(50.779)
subsidies$_t$	0.243***	0.179***
	(12.949)	(7.639)
Constant	0.754***	-3.829***
	(12.773)	(-42.517)
Controls	Included	Included
Cluster by firm	Yes	Yes
Observations	73,925	73,925
Adj. R2	0.457	0.133

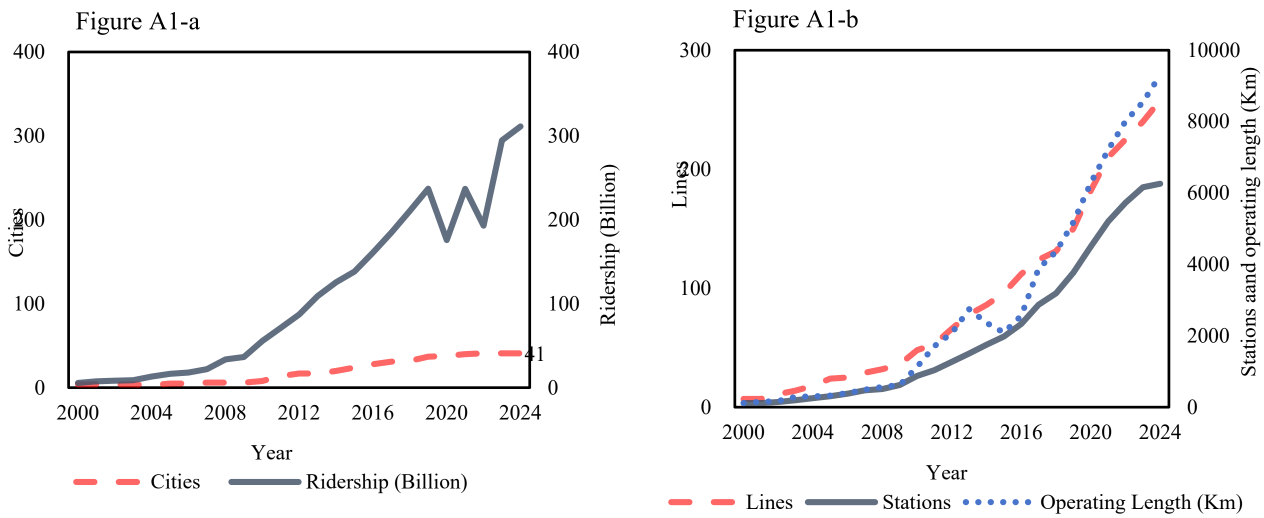
Notes: This table reports the Heckman regression results on the association between subway station construction and collateral purchases. Column (1) reports the estimation results of subway station construction and productive structure purchase (*building_purchase*). Column (2) reports the estimation results of the subway station construction and land purchase (*landuse_purchase*). The sample period spans 2007-2016. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. All regressions include year and firm dummies, although their coefficients are not reported for brevity. t-statistics are computed using robust standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A8: Firms' collateral assets and financing

Variables	(1) Dependent variable = *Liability_ratio*$_t$	(2) Dependent variable = *Liability_ratio*$_t$
building_value$_t$	4.593***	
	(39.498)	
landuse_value$_t$		6.245***
		(11.320)
Constant	-5.560	-0.512
	(-0.689)	(-0.062)
Controls	Included	Included
Firm FE	Included	Included
Year FE	Included	Included
Cluster by firm	Yes	Yes
Observations	73,626	73,626
Adj. R2	0.270	0.258
Mean of dep. var.	34.583	34.583

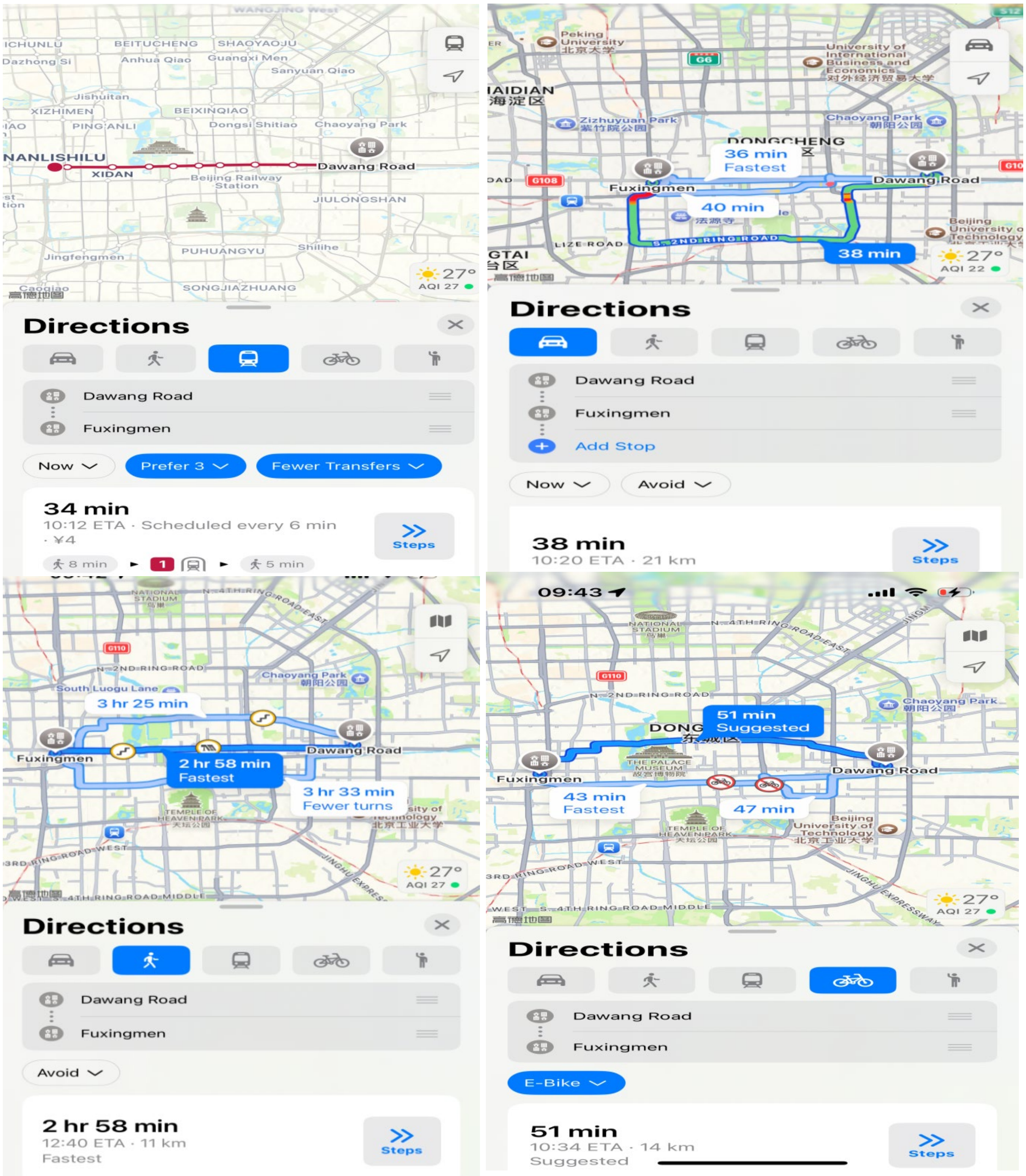
Notes: This table reports the estimation results for the association between subway station construction and firms' collateral assets. Column (1) reports the results of the baseline regression augmented by *building_value* but excluding *Treat*×*Post*. Column (2) reports the results of the baseline regression augmented by *landuse_value* but excluding *Treat*×*Post*. The sample period spans 2007-2016. Continuous variables are winsorized at the 1st and 99th percentiles, with detailed definitions provided in Appendix Table A3. All regressions include year and firm dummies, although their coefficients are not reported for brevity. t-statistics are computed using robust standard errors adjusted for heteroskedasticity and clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure A1: Subway construction in China



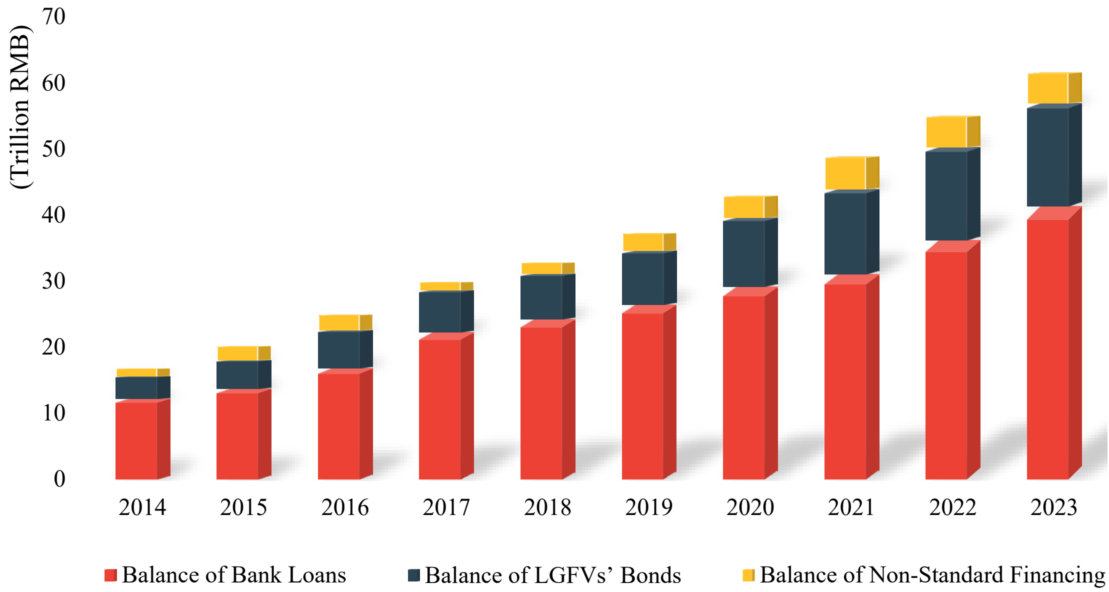
Notes: This figure illustrates the development of China's subway system over time. The left panel plots the number of cities with operational subway systems (left axis) and total subway ridership in billions of passengers (right axis) from 2000 to 2024. The right panel shows the growth of the number of subway lines (left axis), stations, and total operating length in kilometers (right axis) over the same period. The data indicate a sustained expansion of China's subway network in both coverage and capacity, particularly after 2007. Sources: Statistical Yearbooks of Chinese Cities and the official website of the Association of Metros (www.camet.org.cn/).

Figure A2: Commuting transport options between two representative locations in Beijing (Distance ≈ 15 km)



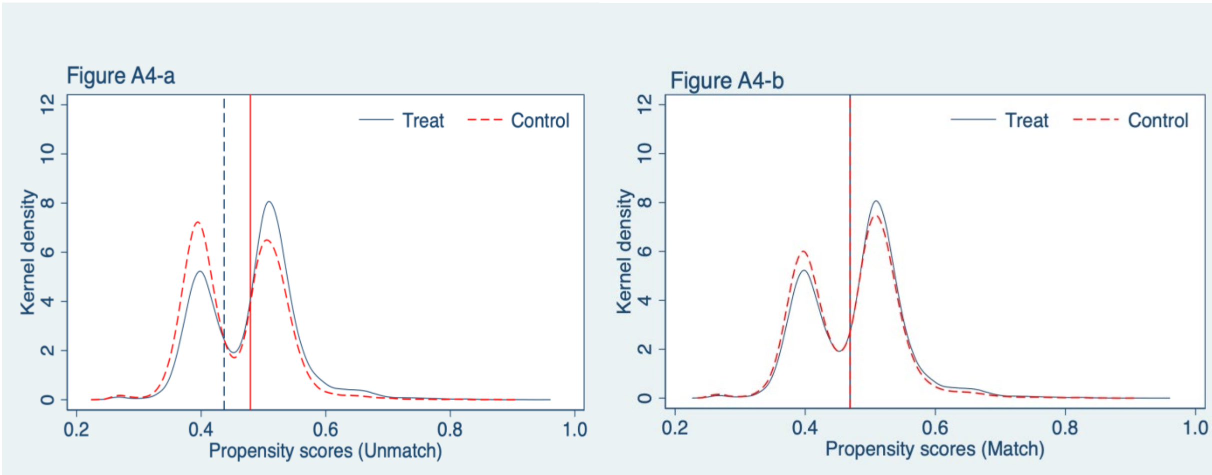
Notes: This figure presents the spatial relationship based on a representative travel time of each transport mode. The figure focuses on two subway stations in Beijing, i.e., Dawang Road and Fuxingmen, located roughly 15 kilometers apart. The comparison covers five transport modes: (i) subway (34 minutes), (ii) private car (38 minutes), (iii) walking (2 hours 58 minutes), (iv) bus (3 hours 25 minutes), and (v) e-bike (51 minutes). Travel times are estimated using Apple Maps as of May 2026, under typical weekday morning traffic conditions.

Figure A3: Local Government Financing Vehicles (LGFVs)' Interest-bearing debt balance in China



Notes: This figure presents the composition and evolution of Local Government Financing Vehicles (LGFVs) financing in China from 2014 to 2023. The total financing balance is decomposed into three components: bank loans, LGFVs' bonds, and non-standard financing instruments. The data reveal a steady expansion in debt, primarily driven by the continuous increase in bank loans and LGFV bond issuance, while non-standard financing shows relatively moderate growth after 2020. Sources: Enterprise Early Warning System (www.qyyjt.cn).

Figure A4: Kernel density distribution of propensity score matching

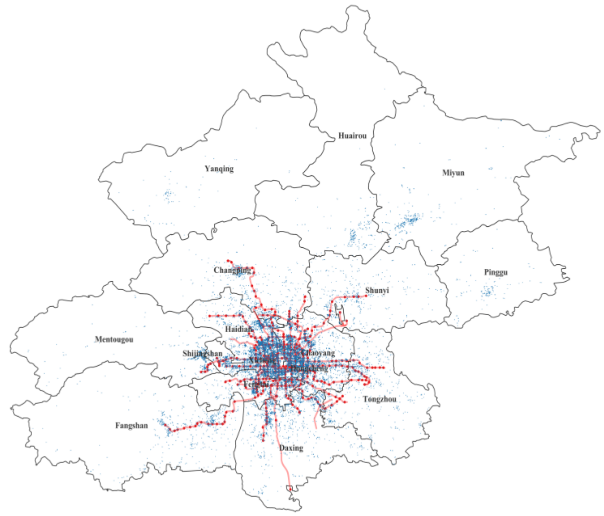


Notes: This figure shows the distribution, in the form of kernel density curve, of propensity scores for the treatment group and control group before and after the matching. The horizontal axis represents the propensity scores; the vertical axis represents the probability density. The left (right) figure shows the distribution of propensity scores before (after) the matching. The treatment indicator variable, *Treat*, equals 1 (0) if a firm is located within (outside) a 1-kilometer radius of a newly opened subway station built in 2007-2016. *Post* is the time indicator which equals 1 (0) if the year is in the post- (pre-) event period. The solid (dashed) curves represent the distribution of propensity scores for the treatment (control) firms. We follow Sager and Singer (2023), Boehm et al. (2025), and Tricaud (2025) to match each treatment firm, with replacement, with a control firm by using the closest propensity score within a caliper of 1% for each year.

Figure A5: The Distribution of MCT and service firms in Beijing and Shanghai

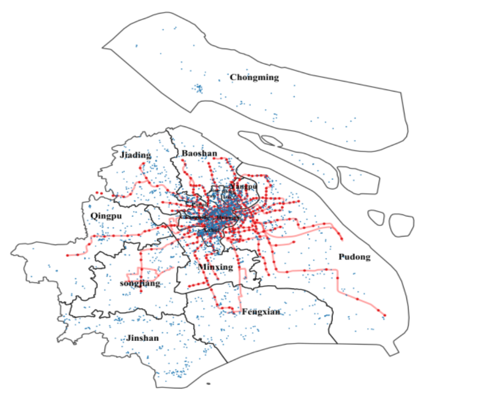
(*a*) MCT private firms in Beijing

(*b*) Service private firms in Beijing



(*c*) MCT private firms in Shanghai

(*d*) Service private firms in Shanghai



Notes: This figure presents the spatial distribution of subway networks and private firms in the manufacturing, construction, and transportation (MCT) sectors, as well as in the service sector in Beijing and Shanghai. The subway lines are for 2016, and the distribution of firms is the average for the period 2007-2016. The red lines represent subway routes, red dots indicate subway stations, and blue dots denote the locations of private firms. Sources: firm-level data are obtained from the National Tax Survey Database (NTSD), subway information comes from Statistical Yearbooks of Chinese Cities and the official website of the Association of Metros (www.camet.org.cn/).