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Infrastructure as Financial Accelerators: Evidence from Subway Construction in Chinese Cities

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Keywords: government investment; financial accelerators; subways; private-firm financing; collateral values
JEL Classifications: G12; G14; G18

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1. Introduction

Prior literature has extensively explored the costs associated with government spending, highlighting its crowding-out effects on private-sector commercial activities.[1] However, government investment is often directed toward infrastructure construction (e.g., public roads, highways, railways, and subways), which can also increase the economic value of nearby private-sector assets that it serves. 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 it is a secondary effect, can lead to significant pro-cyclical consequences in a rapidly urbanizing economy facing financial frictions, much like the financial accelerator mechanisms in a mature economy (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Bernanke et al., 1999).[2]

In this study, we exploit China's large-scale subway expansion following 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 certain location, the introduction of a subway station is an external shock, so we can employ a difference-in-differences (DID) research design to study the impacts

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[1] 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).

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

of government investment. Meanwhile, subway systems, as a prevalent government investment, are typically located in densely-populated urban areas and stimulate high-density, high-value urban commercial activities in adjacent areas. This spatial concentration allows us to precisely measure the proximity of a firm to a nearest subway station, which directly captures variation in the value of land and building-related assets (Baum-Snow and Kahn, 2000; Bowes and Ihlanfeldt, 2001; Gibbons and Machin, 2005; Chu et al., 2021).

Subways may create a financial-accelerator effect for the private sector by increasing the value of their land and buildings. For one thing, by providing convenient, reliable, and affordable station-to-station commuting options, subways significantly extend feasible commuting distances and reduce travel times. This can greatly increase the attractiveness of private-sector firms located close to subway stations for their potential employees, thereby increasing the value of surrounding land and buildings. Empirical research has found that proximity to subway stations generates higher values of buildings and land.[3] For another, commercial activities tend to agglomerate around subway stations and increase the demand for land and buildings in surrounding areas. Given the relatively inelastic supply of urban land and buildings, this surge in demand will be capitalized into the prices of land and buildings around subway stations, thus resulting in substantial land value and building appreciation (Baum-Snow and Kahn, 2000; Bowes and Ihlanfeldt, 2001). Taken together, these effects strengthen the collateral bases of the private sector by increasing the market value of their land and buildings, which, in turn, relaxes borrowing constraints and enables access to more external financing.

[3] For representative studies, see Dewees (1976), Baum-Snow and Kahn (2000), Bowes and Ihlanfeldt (2001), Gibbons and Machin (2005), Chu et al. (2021), Zhou et al. (2021), Gupta et al. (2022), Keeler and Stephens (2023).

The empirical setting of our study is China's private sector. 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. As the credit market is characterized by ownership-based discrimination, state-owned enterprises (SOEs) enjoy relatively easy access to financing, whereas private firms are often required to pledge additional collateral to obtain external funds (Song et al., 2011; Whited and Zhao, 2021; Shi et al., 2023; Hu et al., 2025). Chronic deficiencies in acceptable collateral (usually production structures and land) substantially constrain private firms' access to credit. A field that has been neglected by the existing academic research and policy discussions is the role that government investment has played to enhance private firms' financing capacity. Our study intends to fill this gap.

To conduct our study, we manually collect data on subway lines and stations across Chinese cities between 2007 and 2016. Then we sample around 300,000 private firms from China's annual tax surveys that provide detailed financial data for surveyed firms. Each firm is matched to its nearest subway station and the distance between the firm and the nearest station is measured. In our baseline study, we restrict the sample to private firms located within 5 kilometers radius of any operational subway station, and define the treatment group (control group) as firms located within a 1 kilometer (between 1 and 5 kilometers) radius of an operational station. Then we estimate a firm-level stacked DID model to explore the impact of subway infrastructure on private firms' financing. We find that the debt/asset ratio is 12.44 percentage higher in the treatment group than in the control group. This finding remains robust to propensity score matching, alternative definitions of the treatment and control groups, alternative measures of firm financing, subsample

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

analyses, and placebo tests. Furthermore, we find that the introduction of a new subway station increases the values of private firms' production structures and land if they happen to possess those two kinds of assets. Additional analysis using a Heckman two-step model reveals that proximity to subway stations significantly promotes private firms' purchase of land and construction/purchase of production structures. Those results indicate that subways enhance private firms' financing capacity by increasing the values of their collateral assets.

Our paper contributes to several 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 traditionally associated with government investment, our finding provides a more nuanced perspective when government spending is considered. As the macro-financial literature has revealed, financial accelerators can substantially amplify pro-cyclical fluctuations in the economy. Government-sponsored infrastructure investment is widely recognized 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 of government spending on infrastructure can lead to economic contraction by reducing firms' financing capacity. This contraction can be particularly serious if the reduction of 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 infrastructural projects. Through these results, we contribute to the burgeoning literature on the real economic impacts of public investment.[5]

Second, finding a channel for government investment to affect firm financing, we enhance the understanding of the dynamic interactions between fiscal and monetary policies. Resonating to the empirical research of the financial accelerator literature,[6] 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).

Third, we expand the scope of the literature on private-sector financing in China. In contrast to the existing studies focusing on institutional and macro-financial determinants of private firm financing (e.g., bank credit constraints, property rights, 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 private firm financing. While government investment may crowd out private-sector investment at the macro level, private firms benefiting from government investment could obtain better financing positions through the financial-accelerator channel. Our results are especially relevant for emerging economies where infrastructure deficits and private-sector financing frictions frequently coexist. As China's case

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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), Barwick et al. (2024).

[6] There is a rich literature of empirical research 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).

has proved, economic takeoff can be accelerated if a country starts with some key geographic regions. Our results thus offer a potential pathway to break the vicious cycle of underinvestment in public infrastructure and credit rationing in those 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 discusses the potential mechanisms. Section 6 concludes the paper.

2. China's subway expansion

2.1. An account of the expansion

Subways are important transportation facilities in modern cities. China's subway system has undergone more than four decades of development. The first subway line, finished 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 operational subway systems, comprising seven lines and 114 stations, with a combined network length of fewer than 150 kilometers and annual ridership below one billion trips.

The phase of rapid subway development started in 2007, a year before the 2008 Beijing Summer Olympic Games, when Beijing expedited subway construction to improve the connectivity between major stadiums and residential districts. In response to the 2007-2008 global financial crisis, the Chinese government introduced a RMB 4-trillion (US$586-billion) stimulus package to further expand subway infrastructure.[7] The goal was to add 10,000 kilometers to the urban rail transit networks by 2025.[8] By the end of 2024, this ambitious goal was nearly accomplished, with 41 cities operating more than 258 lines and approximately 6,300 stations, totaling around 9,306 kilometers of track. Correspondingly, annual subway ridership increased to approximately 31 billion trips. Figure 1 and Figure A1 illustrate the speed of expansion of China's subway networks from 2000 to 2024.

[Figure 1 about here]

Subways have become a dominant mode of urban transport in major Chinese cities due to their technological and economic advantages, including high-speed operation, safety and reliability, large passenger capacity, high punctuality, and 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 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. Businesses located close to subway stations thus enjoy a transport-accessibility premium, which could manifest in increased customer flows, higher building values, and appreciation in surrounding land prices.

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[7] Of the total funds, RMB 1.87 trillion (46.8 percent) 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 percent) 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.

[8] 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.

Subway construction is extremely 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.[9] 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 similar to state-owned enterprises – as quasi-fiscal instruments to raise funds without formally recording budget deficits. According to one source, LGFVs' interest-bearing debt financing had surged to RMB 61.56 trillion by 2023, of which bank loans accounted for RMB 41.32 trillion, representing 63.92% of the total interest-bearing financing (see 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).[10] However, as a substantial portion of this debt finances infrastructure construction, the private sector may simultaneously benefit through the financial-accelerator channel proposed in this paper.

2.2. Regional distribution of subways and private firms

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

[10] 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.

A city has to get approval from the central government if it wants to build a new subway line. A team commissioned by the central government will conduct a comprehensive assessment on the city's fiscal capacity, gross regional product, population projection, and other factors.[11] Consequently, the distribution of subways across China has been highly uneven (Figure 1). First-tier cities such as Shanghai, Beijing, and Shenzhen feature dense and well-developed subway networks, whereas many western cities possess only limited or fragmented systems. Within cities, subway networks have expanded from single-line routes to more complex circular-radial networks. Correspondingly, subway stations have evolved from isolated transport facilities into integrated intermodal hubs connecting railways, 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 broader geographical coverage. Firms are particularly concentrated in cities with extensive subway networks, especially in major metropolitan areas such as Beijing and Shanghai. Within these cities, firms also tend to cluster along subway corridors or around station areas. Figure 2 plots the distribution of private firms relative to subway lines in Beijing and Shanghai between 2007 and 2016. In both cities, firm density was high in downtown areas where subway lines were also dense, and it declined toward the suburban areas. In Beijing, there was no clear sign of firms' agglomerating along subway lines. This was also true in downtown Shanghai. But in suburban Shanghai, firms did tend to locate around subway lines and near their terminal stations.[12]

[11] 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.

[12] The different patterns in Beijing and Shanghai are created by the two cities' different approach to city planning. Beijing has expanded in almost all directions and no clear satellite cities exist. Shanghai has deliberately developed several satellite cities and connected them with the city center by highways and subways.

[Figure 2 about here]

A crucial challenge to our identification strategy is whether the distribution of subway stations is endogenous to economic and commercial activities. If subway stations are disproportionately located in areas where economic and commercial activities are already more active than other areas, the impacts of subway stations that we will find may be created by the existing prosperous activities, not the stations themselves. The agglomeration of firms that we've found in Figure 2 lessens the concern (for example, it is hard to imagine that firms were first established on a line in suburban Shanghai and then a subway line was built along it). But we will carefully design our empirical strategy to take care of the endogenous issue.

3. Data and methodology

3.1. Data sources and sample selection

The data used in our study cover the period 2007 – 2016.[13] Firm-level data are drawn from the National Tax Survey Database (NTSD), a unique, comprehensive, and largely under-explored 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 firm characteristics, operations, and financial performance. It encompasses over 400 high-precision and rigorously validated indicators, including taxes, balance sheets, income statements, and cash flow statements, etc.[14] In addition,

[13] The NTSD started in 2007. The latest publicly available data are for 2016.
[14] 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

the NTSD covers above-scale as well as small, medium, and micro enterprises in all prefecture-level cities and across all sectors, thus exhibiting strong representativeness at both the regional and industry levels, better than other widely used datasets such as the Annual Survey of Industrial Firms. Because the NTSD does not provide geographic coordinates of each firm, we match firms in the NTSD with the official business registration records to retrieve their registered addresses and then use both the registered address and firm name to obtain a firm's geographic coordinates via geocoding APIs provided by Amap (Gaode Maps) and Baidu Maps.[15]

We define subway systems to include both above-ground light rails and underground subways, but exclude trams. To complement the firm data, we manually collect annual information on each city's subway system, including subway lines, stations, and their construction start and completion dates, from official metro and government websites.[16] 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. Among the stations, 381 were already operational at the start of our sample period. Of these, 293 remained unchanged with no newly planned subway lines passing through in our sample period, while 88 experienced the addition of new lines passing through. In contrast, construction

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, ensuring each fixed asset transaction is backed by verifiable VAT invoices, thereby deterring overreporting. 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 strengthening data integrity in the NTSD.

[15] 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 by 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.

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

of the remaining 5,879 stations started during the sample period, but only 1,952 were opened during the sample period, while the remaining 3,887 remained unopened by the end of the sample period.[17] Accordingly, our analytical sample consists of 2,333 stations that were operational at any point between 2007 and 2016 (i.e., the initial 381 stations that were open before 2007 plus the 1,952 stations that were newly opened in our sample period), distributed in 27 mainland cities. Table A1 presents the details on the operation of subway lines in China.

A firm's subway distance is measured as the geodesic distance between its registered address and the nearest subway station that was operational in the same year. To compute this distance, we employ the "Near" analysis tool in ArcToolbox using ArcGIS 10.8 to calculate the shortest linear (straight-line) distance from each firm to the closest subway station in its city for each year of observation, based on the annually updated data of operational subways. For a firm located in urban areas without new or closer operational stations throughout the sample period, the identity of the nearest station remains unchanged. Consequently, these firms are assigned a fixed distance that does not vary across years, yielding a single unique distance value in the panel dataset.[18] By contrast, for firms situated in urban areas where subway infrastructure expanded over time, the nearest operational station may change from year to year,, leading to annual updates to the measured distance. Typically, the distance decreases when a new and closer station becomes operational.[19]

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

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

[19] To illustrate this point, consider firm X, which is observed continuously from 2011 to 2013. Before June 1, 2012, the nearest station (Station0) was 2.7 kilometers from the firm. On June 1, 2012, a new subway line was built, and a new station (Station1) 1.8 kilometers away from the firm came into use. Opening at the same time was another new station (Station2) 3.6 kilometers away. Subsequently, on May 1, 2013, a third new station (Station3) 1 kilometers away came into use. In this case, the firm's distance to the subway in 2011, 2012, and 2013 is recorded as 2.7 kilometers, 1.8 kilometers, and 1 kilometers, respectively.

One of the drawbacks 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, firms may have certain data deficiencies that render those firms 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 subways by 2016. We do this because firms in cities without subways would all belong to the control group, but cities may differ substantially and our estimates for the effects of subways may pick up those differences. This leaves us with 314,997 firms appearing in the sample period, contributing 624,676 firm-year observations. Second, we exclude firms that did not appear in the sample for at least five years. With this exercise, we build an unbalanced panel structure for our sample. Third, we drop firms with inconsistent registration locations to ensure accurate spatial alignment with subways. Fourth, we eliminate observations from firms 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 less than the current period's depreciation expense). Fifth, we exclude firm-year observations with missing values for the key variables to be used in our regression analysis. Luckily, there are not many of such observations. After these steps, the sample consists of 20,198 firms located in cities with operational subway systems, contributing 116,766 firm-year observations. Finally, for baseline analysis. we limit the range of firms to those located no more than 5 kilometers away from the nearest subway station. We do this because firms located further away from subway stations are most likely situated far away from the urban periphery or satellite centers. Their surrounding areas may have lower land prices and real estate values, making them less comparable to areas close to 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 1.

Finally, annual city-level socioeconomic data are sourced from the *China City Statistical Yearbook* and the *China Urban Construction Statistical Yearbook*. Those data are matched to 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 approximate bank loans by the difference (denoted by *Liability*) between a firm's total liabilities and its accounts payable because bank loans and accounts payable are the two major forms of external financing available to firms. Based on this proxy, 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 borrowings.[20]

3.3. The empirical strategy and variables

Given the staggered timing of the introduction of subway stations, we adopt a stacked DID specification to evaluate the economic impact of subway stations on private firms' financing outcomes. The DID specification requires identifying the treatment (control) group, of which firms

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

are (not) subject to the introduction of a nearby 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 an operational subway station built between 2007 and 2016. We do it because 1 kilometer is considered as an acceptable pedestrian commuting distance (Gibbons and Machin, 2005).[21] In our robustness checks, we will try other definitions of the treatment (control) group.

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

[Table 1 about here]

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

$$Liability\_ratio_{i,t} = \alpha + \beta Treat_i \times Post_t + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where the dependent variable is private firms' financing (*i*.e., *Liability_ratio*). $Treat_i$ is an indicator that equals 1 (0) if a firm *i* is located within (more than) 1 kilometer radius of an operational subway station built between 2007 and 2016. $Post_t$ is a time indicator which equals 1 (0) if year *t* falls in or after (before) the year in which the station opened between January and June, or equals 1 (0) if year *t* is the year after (in or before) the year in which the station opened between

[21] It takes 10 to 12 minutes for a typical adult to walk 1 kilometer. City plans for Beijing and Shanghai require that subway stations be reached by 10 minutes walk for people living in any downtown neighborhood.

July and December.[22] 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 variables that may affect private firms' financing, including firm size (*size,* the natural logarithm of firms' total assets), rate of return on assets (*roa,* 100 times firms' net profits divided by total asset), sales growth (*sales_growth,* 100 times the difference between firms' sales in the current fiscal year and the previous year, 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), the industry concentration (*hhi,* firms' sales in each industry), tax payment (*tax*, the natural logarithm of firms' total tax expenditure), population density (*population*, number of people living in a city per square kilometer of land area), second industrial ratio (*second_industrial_ratio*, 100 times the city's secondary industry divided by total regional gross domestic product), and regional economic vitality (*light*, a city's nighttime light). We also include firm and year fixed effects to control for time-invariant firm characteristics and common time trends. To avoid the impacts of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles. Detailed definitions and summary statistics of all variables are provided in Appendix Table A4, respectively. To account for potential heteroscedasticity and serial correlation, standard errors are clustered at the firm level throughout the regression analysis.

[22] Considering that subway stations near firms may open close to the beginning or the end of a year, the economic data for that year may not fully capture their economic effects. To avoid potential bias, we use June 30 as the cutoff date.

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 for 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-level 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_A1*, *Liability_A2*, *Liability_A3*, and *Liability_A4*, and rerun Model (1). *Liability_A1* is the natural logarithm of *Liability*. This measure includes the size effect of firm operation which is neutralized by *Liability_ratio*. *Liability_A2* is a firm's annual borrowings divided by its total assets. It reflects a firm's ability to obtain interest-bearing liabilities. Higher values of *Liability_A1* and *Liability_A2* indicate higher financing ability for private firms. *Liability_A3* is interest expenses divided by a firm's total debt, and *Liability_A4* is financial expenses, also divided by a firm's total debt. Those two variables capture firms' cost of financing controlling their debt levels. Therefore, their high 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 conform to our expectations. For example, in Column (3), being close to a subway station is found to cause an increase to the total liability by 12.17 percent of the sample mean, stronger than the baseline estimate. The cost-saving benefit is also statistically significant. Specifically, in Column (4), the reduction of interest payments is only 20.21 percent of the outcome mean. Those two contrasting results make sense. Subway stations increase firms' collateral values, and higher collateral values enable firms to borrow more. But it is less clear whether higher collateral values lower firms' financing costs.

4.2. Testing pre-trends

Our DID specification is subject to the challenge that the construction of subway stations is endogenous to the prosperity of neighborhoods. Specifically, subway stations may be deliberately built in more commercial neighborhoods where property and land values would increase faster than in other neighborhoods even without a subway station. In the rest of this section, we will perform careful robustness checks to deal with this challenge.

In this subsection, we first perform an event study to test the 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 exhibited similar trends between 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, in the literature researchers often test whether there are pre-trends before the treatment (e.g., Beck et al., 2010). Following the literature, we conduct the following event study:

$$\text{[illegible]}\_\text{[illegible]}_{\text{[illegible]}} = \beta_0 + \beta_1 Pre6\_\text{[illegible]} + \beta_2 Pre5 + \beta_3 Pre4 + \beta_4 Pre3 +$$

$$\beta_5 Pre2 + \beta_6 Pre1 + \beta_7 \square\square\square\square\square\square\square + \beta_8 Post1 + \beta_9 Post2 + \beta_{10} Post3 + \beta_{11} Post4 + \beta_{12} Post5 + \beta_{13} Post6\_\square\square\square\square + \square\square_{\square,\square} + \square_{\square} + \square_{\square} + \square_{\square,\square} \quad (2)$$

where *Pre**, *Current*, and *Pre** are indicator variables representing the years before, in, and after the year in which a nearby subway station was opened.

Figure 3 provides a visual presentation of the estimation results of Model (2). Prior to the operation of a nearby subway station, there is no significant difference between the treatment group (i.e., firms located within 1 kilometer of the station) and the control group (i.e., firms located beyond the 1 kilometer radius). In contrast, following the operation of a nearby station, the treatment effect becomes pronounced and persists over time. Therefore, our event study has excluded the confounding effects of pre-trends. This result raises our confidence that our estimator is not subject to the endogeneity concern.

[Figure 3 about here]

4.3. Propensity score matching

Next, we use propensity score matching (PSM) to construct a more comparable treatment group and implement the DID analysis again. Specifically, we perform 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 its closest control firm (i.e., a firm located outside the 1 kilometer radius of an operational subway station) based on the propensity scores estimated for the corresponding treatment year. To ensure high matching quality, we impose a strict caliper equal to 1% of the standard deviation of the estimated propensity scores. The set of covariates used for propensity score estimation includes firm size (*size*), sales growth (*sales_growth*), ccash holdings (*cash*), the degree of industry competition (*hhi*), as well as firm tax

(*tax*). Following the matching procedure, we construct a matched sample comprising 38,097 firm-year observations from 11,505 firms.

To assess the quality of the propensity score matching procedure, we examine the the extent of overlap in the propensity score distributions of 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 the matching, As shown in Figure A4-*b*, the distributions converge substantially, indicating improved comparability. The matching will certainly not eliminate the concern of endogeneity (because the treatment and control groups are defined by geographical distances, which are not included in the matching process), but will improve the quality of our DID estimator.

Table A5 reports two sets of results of the DID estimation using the matched sample. Columns (1) does not include any control variables, and Column (2) does. The magnitude of the DID estimator has been substantially increased compared with the baseline result. Although we don't take this as evidence for the exogeneity of subway construction, the PSM result does boost our confidence that subway stations increase firms' financing capacity.

4.4. Alternative definitions of the treatment and control groups

Our next robustness check is to study whether the baseline results are sensitive to different definitions of the treatment and control groups. Although 1 kilometer is regarded as the proper distance for pedestrian commuting, using this threshold to define our treatment group may still be somewhat arbitrary. To this end, we 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 those two alternative definitions. In addition, we narrow and expand the radius of the control group to see how our estimator changes. Specifically, we restrict the sample to firms located within 3 kilometers, within 10 kilometers, and more than 1 kilometer from an operational subway station without imposing an upper distance limit (beyond 10 kilometers). For each subsample, the control group consists of firms not located within 1 kilometer of an operational subway station.

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 levels of significance have declined. The first estimate (when the radius is 1.5 kilometers) is larger than the second estimate (when the radius is expanded to 2 kilometers), and both of them are smaller than the baseline estimate. This pattern indicates that the DID estimate declines as the treatment radius expands, confirming our conjecture that the effect of subway stations attenuates when the treatment group is broadened. Interestingly, a similar pattern is also found when the control group is redefined. Columns (3) and (5) present the results when the control group is defined as firms located 1–3 kilometers, 1–10 kilometers, and beyond 1 kilometer radius without imposing an upper distance bound from an operational subway station, respectively. The three estimates follow a declining order, and the baseline estimate (when the control group is defined as firms located 1–5 kilometers radius) fits perfectly between the first estimate (when the control group defined as firms located 1–3 kilometers radius) and the second estimate (when the control group defined as firms located 1–10 kilometers radius). That is, the impact of a subway station is stronger when the control group is more confined to firms located more closely to it. These results strengthen our confidence in the baseline estimation in two ways. First, they contradict the conjecture that our baseline results stem from the tendency of subway lines and station to pass through more prosperous neighborhoods. If that were the case, narrowing the control radius toward the stations would weaken the estimated effects, as firms in the control group would more closely resemble treated firms and benefit more from the underlying prosperity. However, we observe the opposite. Second, firms in the control group should become more comparable to firms in the treatment group when the size of the control group becomes smaller. In light of our PSM results, this should lead to stronger estimates. But this is what we have just found.

[Table 3 about here]

4.5. Subsamples analysis using mco-sector firms and service-sector firms

The validity of our causal inference in the DID analysis may still be compromised by the endogeneity problem of subway site selection. Intuitively, subway stations are often constructed in economically vibrant urban centers, where intensified commercial activity naturally raises surrounding asset values. Thus, the observed improvement in private firms' financing—through increases in collateral values—may reflect pre-existing locational advantages rather than the causal effect of subway stations themselves.

To address this potential confounding factor, we conduct sub-sample analyses for firms in the manufacturing, construction, and transportation (mco) sectors, as well as for those in the service sector. In China, mco-sector firms require extensive production structures and substantial land resources; they therefore tend to locate in peripheral urban areas, suburban zones, or designated industrial parks where factory space and land are more affordable and suitable for large-scale operations. In contrast, service-sector firms depend heavily on direct customer flows, leading their headquarters to cluster in central business districts, which offer the highest concentration of potential consumers. Figure 4 illustrates these distinct spatial distribution patterns using Beijing and Shanghai as representative examples.

The sub-sample regression results are reported in Table 4. Column (1) presents the estimates based on the mco-sector firms, while Column (2) reports the results for the service-sector firms. In both columns, the coefficients are positive and statistically significant. Moreover, the magnitude of the DID estimator in Column (1) for mco-sector firms is substantially larger than that in Column (2) for service-sector firms, indicating that the observed increase in private firms' access to financing is indeed attributable to subway construction rather than underlying locational characteristics.

[Table 4 about here]

4.6. State-owned enterprises as a placebo test

Finally, we conduct a placebo test using state-owned enterprises (SOEs) to strengthen causal identification. As previously deliberated, the financing capacity of private firms is highly responsive to the construction of subway stations because these firms are typically financially constrained. In contrast, SOEs face substantially fewer financing frictions due to implicit government guarantees, which allow them to obtain credit more easily and at lower cost. Consequently, the financing behavior of SOEs should be largely insensitive to changes in collateral value induced by nearby subway stations. Therefore, we expect the 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. Table 5 presents the results of this placebo test. Consistent with our expectations, subway construction does not accelerate the financing of SOEs, which are not subject to binding credit constraints. This finding further corroborates our conclusion that the observed increase in private firms' financing is attributable to the collateral channel activated by subway-station construction.

[Table 5 about here]

5. Mechanism tests: collateral channel

The key premise of our study is that the financial accelerator effect of subways comes from subways' role to increase the firms' collateral value. In this section, we will try to empirically test this premise by filling the middle block of the link, i.e., to show that subway stations improve firms' external financing through the collateral channel. Our empirical strategy comprises two steps. The first step, presented below in Section 5.1, is to show that the construction of subway stations increases the value of firms' collateral assets.

5.1. Subway stations and the value of collateral assets

We focus on two types of assets that Chinese banks predominantly accept as collateral, i.e., production/operational buildings and land owned by firms. NTSD records the net book value of a firm's production- and operation-related buildings at the end of the fiscal year. However, NTSD does not record the market value of firm's land. To address this limitation, we rely on the firms' land-use tax to identify land ownership and to proxy for land value. In China, the land-use tax is levied based on the taxable land value; thus, land-use tax indirectly captures the underlying economic value of land-use rights that a firm holds, as higher land-use tax payments are typically associated with larger or more valuable land parcels.[23]

[23] Formally, a firm's land-use tax equals the product of its taxable land area (measured in square meters) and the locality-specific statutory tax rate. These statutory rates vary across regions and are determined by factors such as infrastructure availability and the level of regional economic development. Land parcels situated near subway stations are often subject to higher statutory tax rates, reflecting their enhanced accessibility and economic potential. For

To see whether subway stations improve the value of firms' collateral assets of production structures and land value, we construct two outcome variables, *building_value* and *landuse_value*, which are, respectively, the natural logarithm of the value of a firm's production/operational buildings and the natural logarithm of land-use tax paid by firms during the fiscal year. Then we run Model (1) on those two outcomes, respectively.

The corresponding results are reported in Columns (1) and (2) of Table 6. The results are very illuminating. Subway stations significantly raise the values of the two kinds of collateral assets. Specifically, firms located within the 1 kilometer radius of a subway station enjoy a 13.4 percent premium in their building values over firms located in the ring between the 1 kilometer radius and the 5 kilometer radius. The effect on land values is much smaller — the premium is only 1.3 percent — though statistically it is highly significant.

[Table 6 about here]

5.2. Collateral assets and external financing

Our next step to show whether collateral assets play a mediating role for subway stations to improve firm financing. To this end, we first regress *Liability_ratio* on *building_value* and *landuse_value*, respectively, in a fixed-effect model. The results are presented in Columns (1) and (2) of Table 7. Because *building_value* and *landuse*_value are themselves outcomes variables influenced by subway construction, these regressions are intended to be suggestive rather than to establish any causal relationship.

[Table 7 about here]

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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).

Next, we conduct a more rigorous analysis to establish a causal relationship between collateral assets and firm financing. To do so, we define two indicator variables, *dummy_building_*2007 and *dummy_landuse_*2007, which equal 1 if a firm owned any building and land by the end of 2007, respectively, and 0 otherwise. Using these two indicators, we conduct two partitions to our sample, firms with versus without buildings, and firms with versus without land. We then rerun Model (1) for the partitioned samples, which from 2008 onwards, to see if subway stations improve firms' external financing in the partitioned samples. Because the ownership of buildings and land is measured prior to the beginning of our sample period, these partitions are exogenous to subway construction during the study window. Therefore, the contrast between the two subsamples defined by *dummy_building_*2007 and the contrast between the two samples defined by *dummy_landuse_*2007 will establish a causal role for collateral assets to mediate subway stations' impacts on firm financing.

Table 8 present the results. Columns (1) and (2) report the results that compare firms with buildings to those without. The contrast is clear: the DID estimator is significantly positive for the first group of firms and is insignificant for the second group. So subway stations only improve firms' ability of external financing when they have collateral assets (in this case, buildings). Columns (3) and (4) provide a parallel comparison for land ownership and reinforce the same conclusion. The DID estimator is positive and statistically significant only for firms that owned land, whereas it is insignificant for firms without land. Together, these results offer compelling evidence that collateral assets serve as a key mediating channel through which subway station construction enhances firms' external financing.

[Table 8 about here]

5.3. Subway stations and the purchase of collateral assets

In addition, we investigate whether the observed increase in the collateral value of production structures and land value is partly attributable to firms' heightened propensity to purchase these assets in response to subway stations construction. On the one hand, the subway stations enhance regional accessibility, reduce transportation costs and shorten employees' commuting times, thereby increasing locational attractiveness of industrial properties in proximity to stations. Anticipating future appreciation, firms may strategically acquire or expand their holdings of station-adjacent production structures and land. On the other hand, subway operation stimulate station-adjacent economic activity by generating additional passenger flows and expanding business opportunities, which in turn further increase firms' demand to purchase these assets. Collectively, this increased purchase activity may contribute to the observed appreciation of the collateral value of production structures and land. To formally test this conjecture, we employ a Heckman two-step sample selection procedure.[24]

In particular, in the first step, we estimate a probit regression for whether the purchase of production structures (*building_purchase*) and land-use rights (*landuse_purchase*) using a comprehensive set of observable firm characteristics as explanatory variables (i.e., all control variables from our baseline regression). However, the Heckman two-step approach requires additional exogenous variables that are correlated with the likelihood of asset acquisition (i.e., *building_purchase* and *landuse_purchase*) but have no direct impact on the market value of the assets themselves (i.e., *building_value* and *landuse_value*). To this end, we employ three

[24] Many firms have no records of purchasing factory buildings or land-use rights, which may introduce non-random selection and potential self-selection bias. As a result, we employ the Heckman two-step sample selection model to address this issue.

instruments for the analysis: (i) whether the firm operates as the industrial firms (*industry_dummy*); (ii) firm age (*firm_age*), and (iii) firms' subsidies (*subsidies*). Specifically, industrial firms are more likely to purchase production structures and land because long-term leasing arrangements may not adequately meet their operational needs. Similarly, older firms with longer operational histories tend to be more financially stable, making them more capable of acquiring such assets for production, operations, and financing purposes. Additionally, firms receiving higher government subsidies possess greater financial capacity to invest in production structures and land. Hence, industrial firms, older firms, and firms receiving higher subsidies are generally more likely to purchase production structures and land-use rights. Meanwhile, these instruments (i.e., industry affiliation, firm age, and government subsidies) should not be correlated with their firm's market value of production structures and land, thus meeting the "exclusion restriction" assumption for an instrument variable. Accordingly, this set of instrumental variables (i.e., *industry_dummy*, *firm_age*, and *subsidies*) are used in Heckman two-step regressions. *industry_dummy* is equals 1 if the firm belongs to the industrial firms and 0 otherwise; *firm_age* is measured as the natural logarithm of the number of years since the firm's establishment; and *subsidies* is measured as the natural logarithm of government subsidies granted to the firm during the fiscal year. Detailed variable definitions are provided in Appendix Table A3.

Column (1) and (2) of Table 9 reports the first-step regression results of Heckman analysis. the coefficients on the instrumental variables, *industry_dummy*, *firm_age*, and *subsidies* are all statistically significant at conventional levels. which industrial firms, older firms, and firms receiving higher government subsidies are more likely to engage in purchasing production structures and land-use rights. Additionally, as anticipated, the coefficient on $Treat \times Post$ is statistically significant and positive, indicating that firms located near subway station are more inclined to purchase such assets.

Column (3) and (4) of Table 6 present the second-step regression results, the coefficient on *Treat×Post* remains significantly positive, reinforcing our earlier findings that subway stations significantly raise the values of the two kinds of collateral assets.[25]

[Table 9 about here]

6. Conclusion

We document a novel collateral channel through which government investment positively affects the private economy. 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 typically associated with government investment, we provide robust evidence of a causal relationship between subway station construction and the acceleration of private firms' financing. We refer to this as the "financial-accelerator effect." Our mediation analysis further reveals that subway station construction enhances the collateral value of production structures and land, thereby facilitating private firms' access to financing. Additionally, we observe that subway station construction significantly promotes the acquisition of production structures and land by private firms, further increasing the collateral value of these assets.

Our findings underscore the complexity of government investment. When operating under

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[25] The *IMR* coefficient in Column (3) and (4) are statistically significant, suggesting that the unobserved factors driving firms' decisions to purchase production structures and land are positively correlated with the value of these assets.

looser budget constraints, governments allocate fiscal resources to infrastructure projects. Such public investment shocks can transmitted and amplify through credit channels, generating substantial crowd-in effects and potentially reinforcing economic boom cycles. These dynamics demonstrate the intricate challenges involved in managing government-led investment. Our results suggest that the design of monetary expansion or tightening cannot be formulated independently of fiscal responses. The interaction between fiscal policy, credit-market transmission, and monetary policy emphasizes the need for integrated macroeconomic management. These results carry broader implications for other countries especially the country undertake large-scale public infrastructure construction. As governments worldwide increasingly prioritize infrastructure development, understanding the macro-financial consequences of public investment becomes critical.

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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*	(2) Dependent variable = *Liability_ratio*	(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 FE	Included	Included	Included	Included	Included	Included
Year FE	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 on private firms' financing. Columns (1)-(2) reports the regression results using *Liability_ratio* as the measure of private firms' financing. Columns (3)-(6) reports the regression results using *Liability_A1*, *Liability_A2* , *Liability_A3*, and *Liability_A4* as the alternative measure 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 (more than) 1 kilometer radius of an operational subway station built between 2007 and 2016. *Post* is the 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: Robustness test as to alternative treatment groups and control groups

	Dependent variable = *Liability_ratio$_t$*				
	(1)	(2)	(3)	(4)	(5)
Variables	Treatment group <=1.5km	Treatment group <=2km	1 < Control group <=3km	1<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 FE	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included
Cluster by firm	Yes	Yes	Yes	Yes	Yes
Observations	73,626	73,626	62761	86948	116766
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 results with alternative definitions for the treatment and control groups. Columns (1)- (2) report the regression results of 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: Robustness test using subsamples of mco-sector firms and service-sector firms

	(1)	(2)
	Mco-sector firms	Service-sector firms
Variables	Dependent variable = *Liability_ratio*	Dependent variable = *Liability_ratio*
Treat×Post	16.359***	3.570***
	(3.367)	(3.245)
Constant	-44.019	44.590***
	(-1.190)	(3.424)
Controls	Excluded	Included
Firm FE	Included	Included
Year FE	Included	Included
Cluster by firm	Yes	Yes
Observations	23821	38721
Adj. R2	0.279	0.294
Mean of dep. var.	34.978	34.241

Notes: This table reports the subsamples regression results. Column (1) reports the results of using mco-sector firms as the sample. Column (2) reports the results using service-sector firms as the sample. 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 5: State-owned enterprises as a placebo test

Variables	(1) Dependent variable = *Liability_ratio*	(2) Dependent variable = *Liability_ratio*
Treat×Post	2.986	2.867
	(1.235)	(1.191)
Constant	37.970***	2.865
	(27.168)	(0.200)
Controls	Excluded	Included
Firm FE	Included	Included
Year FE	Included	Included
Cluster by firm	Yes	Yes
Observations	22,429	22,429
Adj. R2	0.295	0.301
Mean of dep. var.	39.696	39.696

Notes: This table reports the placebo test results using a sample of state-owned enterprises. Column (1) reports the regression results that include Treat×Post and excludes the control variables. Column (2) reports the regression results that include *Treat×Post* and the control variables. 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 6: Subway stations and firms' collateral assets

Variables	OLS regression (1) Dependent variable=*building_value*	(2) Dependent variable = *landuse_value*	Heckman two-stage regression (3) Dependent variable =*building_value*	(4) Dependent variable = *landuse_value*
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 FE	Included	Included	Included	Included
Year FE	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 regression results for the association between subway station construction on firms' collateral assets. Columns (1)-(2) present the OLS regression of the value of production structures (*building_value*) and land-use rights (*landuse_value*) on subway station construction (*Treat×Post*), respectively. Column (3)-(4) present the Heckman regression results of the value of production structures (*building_value*) and land-use rights (*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 7: Firms' collateral assets and financing

Variables	(1) Dependent variable = *Liability_ratio*	(2) Dependent variable =*Liability_ratio*
building_value	4.593***	
	(39.498)	
landuse_value		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 regression results for the association between subway station construction on firms' collateral assets. Columns (1) reports the results of the baseline regression augmented by *building_value* but excluding *Treat*×*Post*. Columns (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.

Table 8: Firms' collateral assets and financing

	Dependent variable = *Liability_ratio*			
Variables	(1)	(2)	(3)	(4)
	*dummy_building*_2007=1	*dummy_building*_2007=0	*dummy_landuse*_2007=1	*dummy_landuse*_2007=0
Treat×Post	9.519**	2.635	12.259**	2.385
	(2.394)	(1.545)	(2.351)	(1.446)
Constant	-139.495**	-214.854***	77.573	-272.257***
	(-2.268)	(-4.179)	(0.833)	(-6.182)
Controls	Included	Included	Included	Included
Firm FE	Included	Included	Included	Included
Year FE	Included	Included	Included	Included
Cluster by firm	Yes	Yes	Yes	Yes
Observations	26,806	43,898	19,738	50,966
Adj. R2	0.225	0.279	0.214	0.275
Mean of dep. var.	30.556	36.502	27.716	36.778

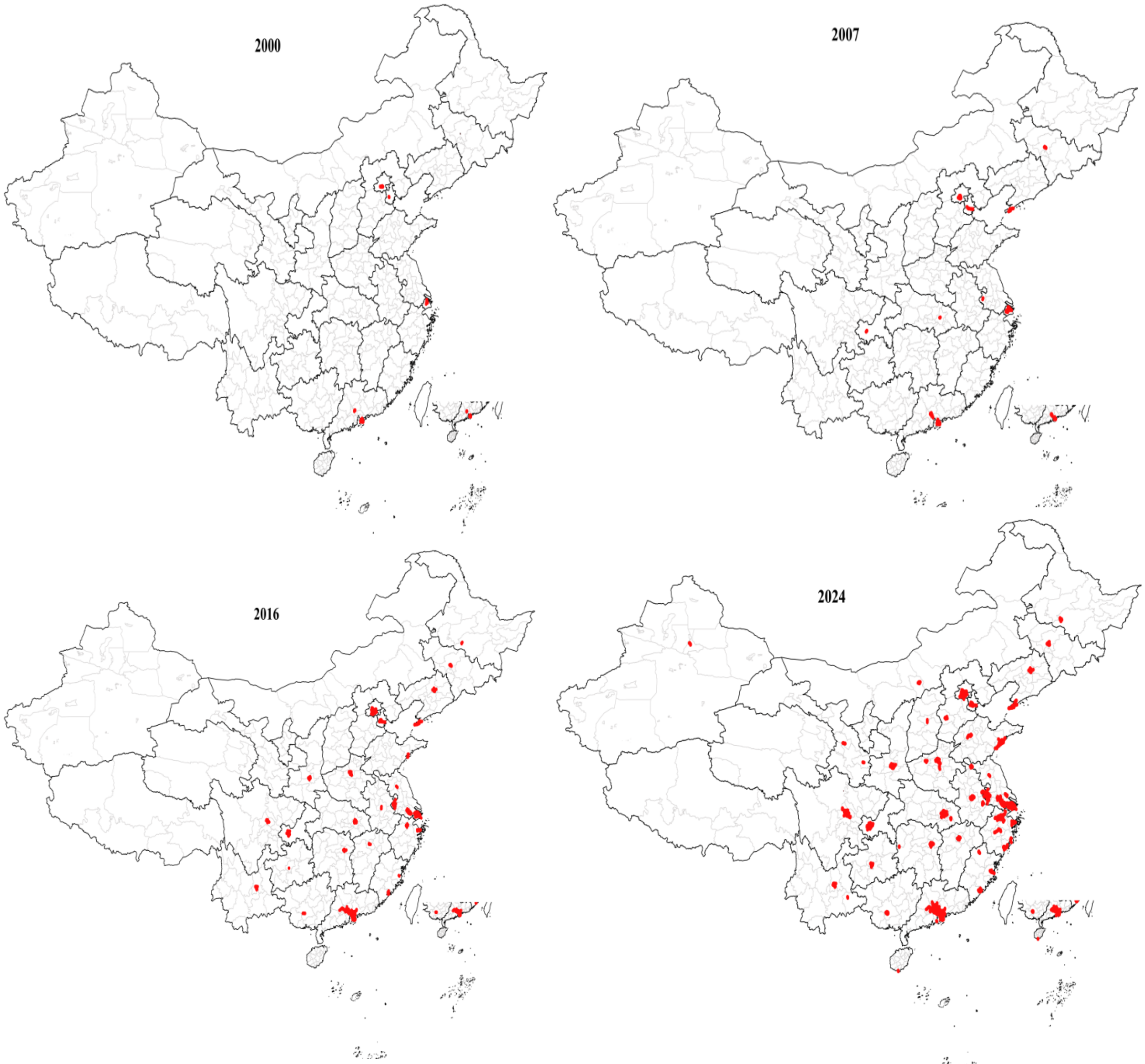
Notes: This table reports the results of the moderating effects of production structures (*dummy_building*_2007) and land (*dummy_landuse*_2007), respectively, in the causal relationship between subways and private firms' financing. Columns (1) and (2) present the results of the baseline regressions estimated for subsamples of firms that own production structures (*dummy_building*_2007=1) and those without production structures (*dummy_building*_2007=0) in year of 2007. Columns (3) and (4) report the results of the baseline regressions estimated for subsamples of firms that own land-use rights (*dummy_landuse*_2007=1) and those without land-use rights (*dummy_landuse*_2007=0) in year of 2007. 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 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.

Table 9: Subway stations and firms' collateral purchase

Variables	Dependent variable = *building_purchase*	Dependent variable = *landuse_purchase*
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 regression results of the Heckman regressions on the association between subway station construction and collateral purchase of factory building and land-use rights values (*building_value* and *landuse_value*). Columns (1) reports the results of the regression results of subway station construction and production structure purchase (*building_value*). Columns (2) report the regression results of the subway station construction and land purchase (*landuse_value*). 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.

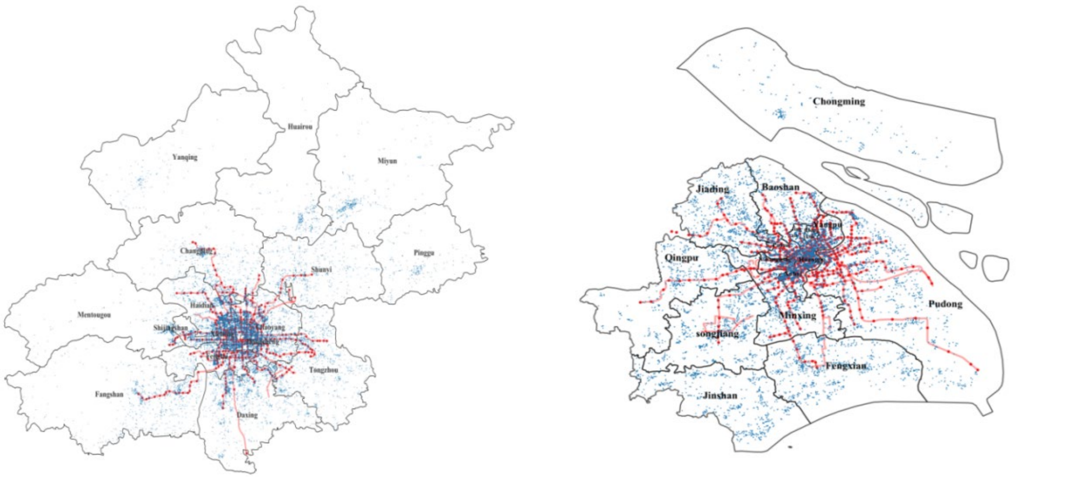
Figure 1: The growth of subway networks from 2000 to 2024



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

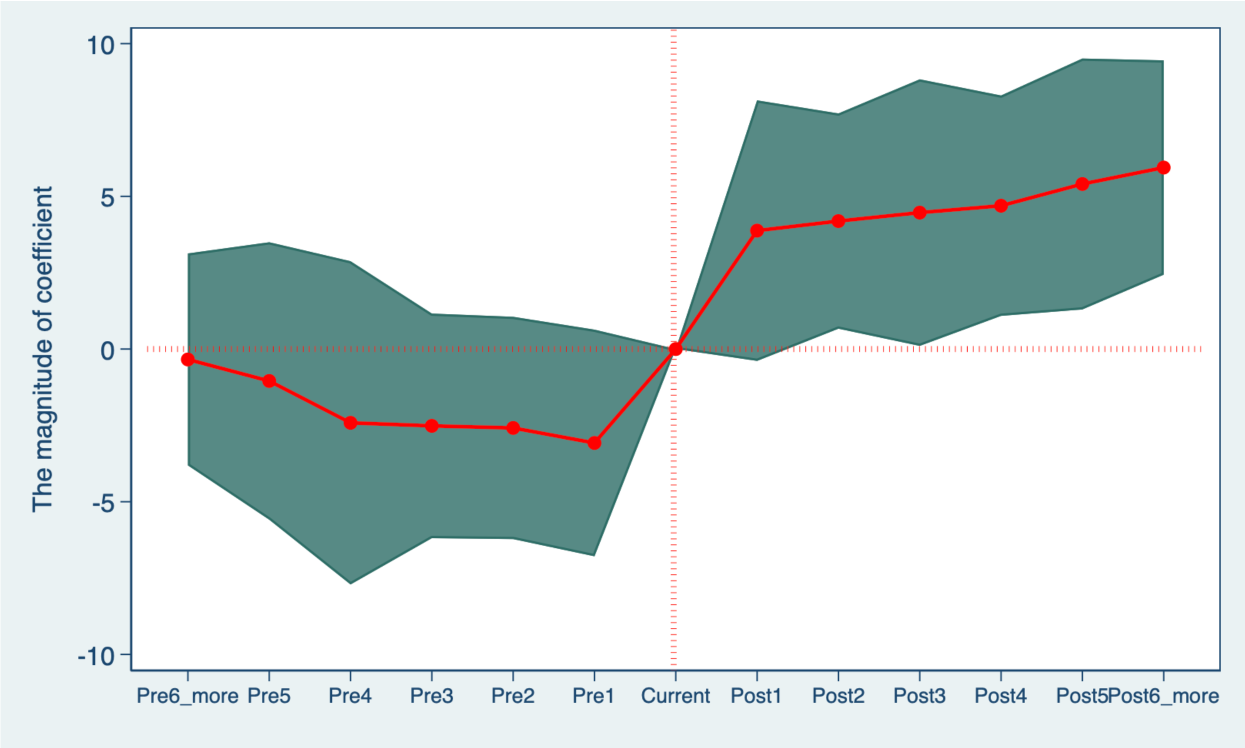
Figure 2: Subway lines and the distribution of private firms in Beijing and Shanghai

(*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 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/).

Figure 3: Results of the event study

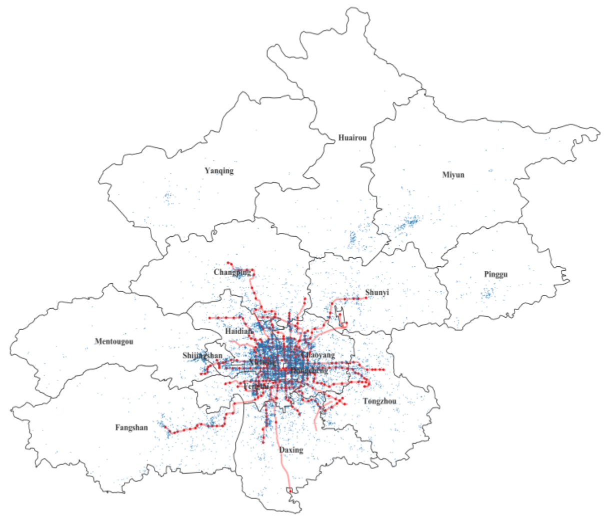


Notes: This figure presents the coefficient estimates and their 95% confidence intervals (shaded areas) based on Model (2). The horizontal axis denotes the year dummies, and the vertical axis represents the corresponding the estimates. The year of the event (the opening of a nearby station) is labeled by *current*. Six years before the event (years before the sixth year are compressed to the sixth year dummy *Pre6_more*) and six years after the event (years after the sixth year are compressed to the sixth year dummy *Post6_more*) are considered. Standard errors of the coefficients are adjusted for heteroskedasticity and clustered at the firm level. Continuz dous variables are winsorized at the 1st and 99th percentiles. Detailed definitions are provided in Appendix Table A3.

Figure 4: Subway Lines and the Distribution of Private Firms in Beijing and Shanghai

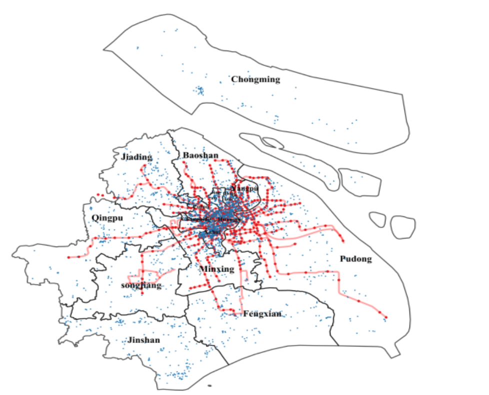
(*a*) Mco private firms in Beijing

(*b*) Service private firms in Beijing



(*c*) Mco private firms in Shanghai

(*d*) Sevirce private firms in Shanghai



Notes: This figure presents the spatial distribution of subway networks and private firms in the manufacturing, construction, and transportation (mco) sectors, as well as those 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/).

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

Tabel 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 an operational subway station.	116,766	20,198
Observations for the main regression include firms located within 5 kilometers of an operational 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_A1	The natural logarithm of the difference between total debt and accounts payable of the firm at the end of a fiscal year.
Liability_A2	100 times the average borrowing, divided by the total assets of the firm at the end of a fiscal year.
Liability_A3	100 times the interest expenses, divided by the total debt of the firm at the end of a fiscal year.
Liability_A4	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 firms are defined as those located within (more than) 1 kilometer radius of an operational subway station built in 2007-2016, when restrict the firms within 5 kilometers of an operational subway station.
Treat1	1 (0) for a treatment (control) firm. Treatment firms are defined as those located within (more than) 1.5 kilometer radius of an operational subway station built in 2007-2016, when restrict the firms within 5 kilometers of an operational subway station.
Treat2	1 (0) for a treatment (control) firm. Treatment firms are defined as those located within (more than) 2 kilometer radius of an operational subway station built in 2007-2016, when restrict the firms within 5 kilometers of an operational subway station.
Treat3	1 (0) for a treatment (control) firm. Treatment firms are defined as those located within (more than) 1 kilometer radius of an operational subway station built in 2007-2016, when restrict the firms within 3 kilometers of an operational subway station.
Treat4	1 (0) for a treatment (control) firm. Treatment firms are defined as those located within (more than) 1 kilometer radius of an operational subway station built in 2007-2016, when restrict the firms within 10 kilometers of an operational subway station.
Treat5	1 (0) for a treatment (control) firm. Treatment firms are defined as those located within (more than) 1 kilometer radius of an operational subway station built 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 operation-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.
building_purchase	1 (0) if a firm does (not) purchase a production structures 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 Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS).
industry_dummy	1 (0) if a firm is (not) belong to industry firm.
firm_age	The natural logarithm of the number of years since a firm's initial established.
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_A1 (ln)	73,626	8.932	0.000	6.240	8.027	9.199	10.444	11.672	15.993	2.655
Liability_A2 (ln)	73,626	38.039	0.000	0.000	0.000	0.000	6.680	51.912	3009.607	210.518
Liability_A3 (%)	73,626	1.306	-10.917	-0.555	-0.035	0.025	1.341	4.170	38.422	5.197
Liability_A4 (%)	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
Treat1	73,626	0.602	0.000	0.000	0.000	1.000	1.000	1.000	1.000	0.489
Treat2	73,626	0.726	0.000	0.000	0.000	1.000	1.000	1.000	1.000	0.446
Treat3	62,760	0.548	0.000	0.000	0.000	1.000	1.000	1.000	1.000	0.498
Treat4	86,947	0.383	0.000	0.000	0.000	0.000	1.000	1.000	1.000	0.486
Treat5	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
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
ln 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

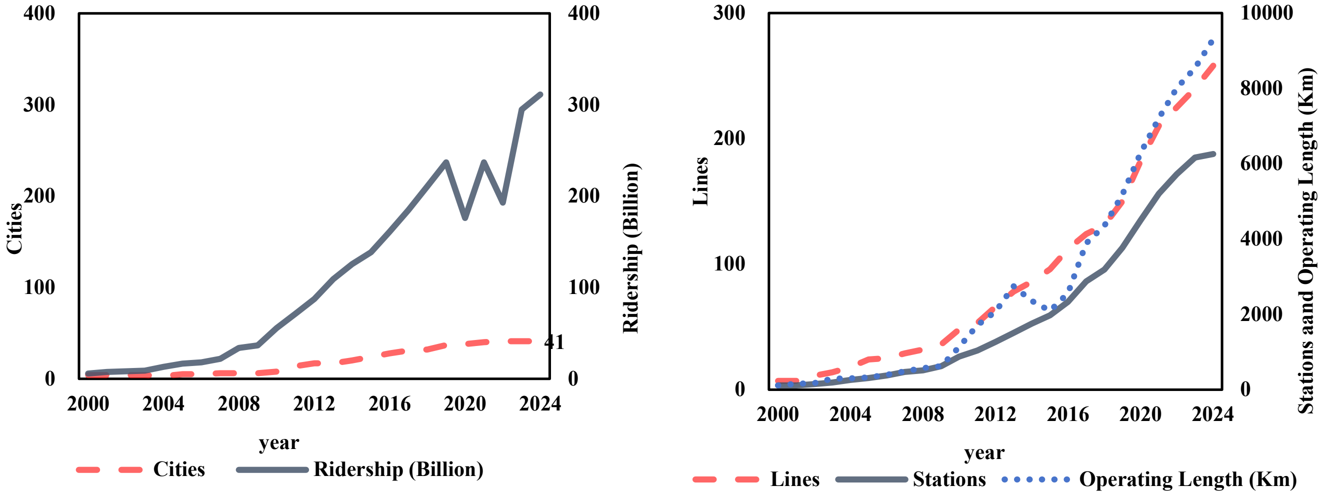
Notes: This table reports the descriptive statistics of all variables used in the multivariate tests of the association between the subway station construction and private firms' financing. Continuous variables are winsorized at the 1st and 99th percentiles points, with detailed definitions provided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

Table A5: PSM results

Variables	(1) Dependent variable = *Liability_ratio*	(2) Dependent variable = *Liability_ratio*
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

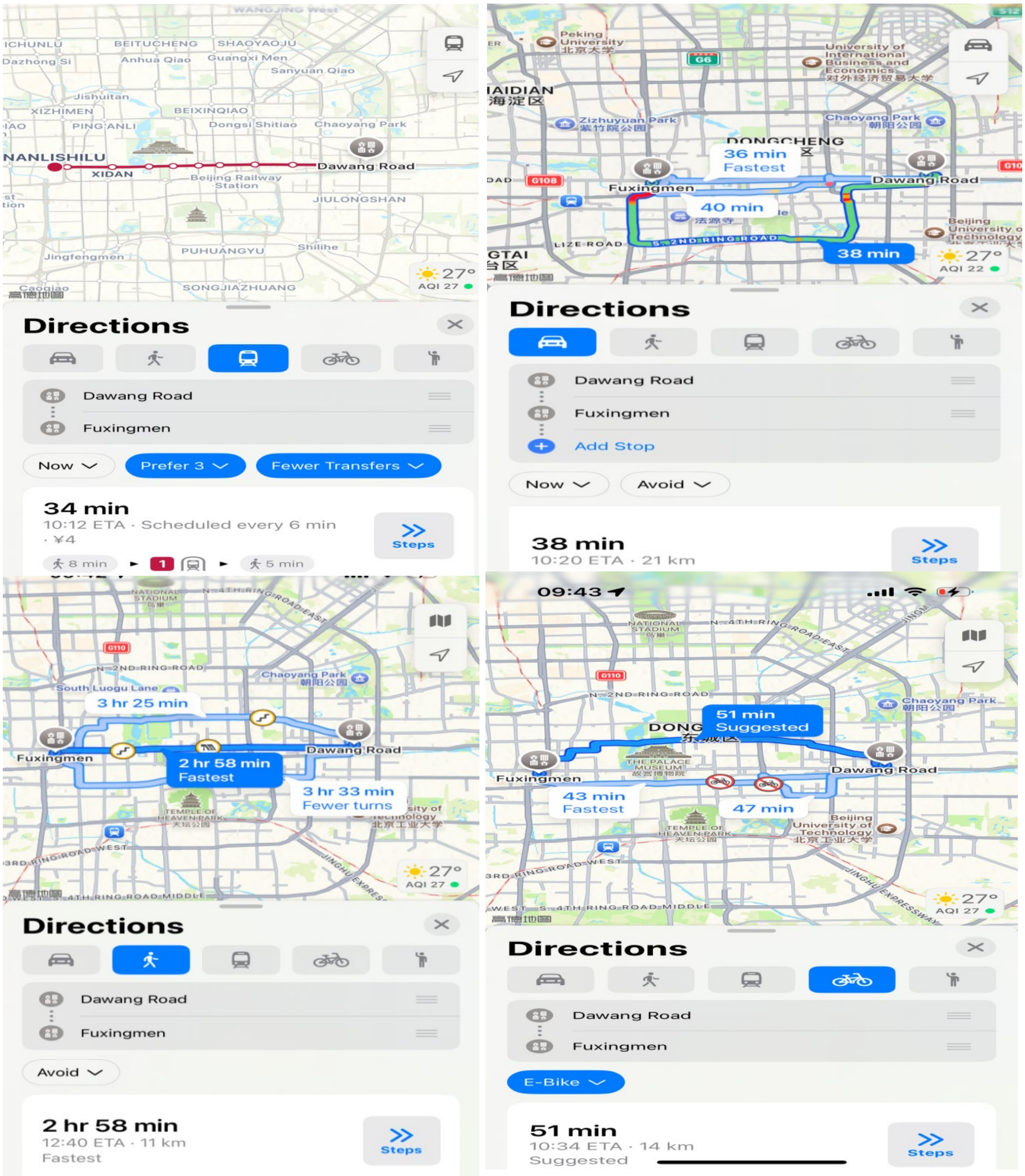
Notes: This table reports the DID results for the PSM sample. Column (1) reports the results of the univariate regression that includes Treat ×Post and excludes the control variables. Column (2) reports the results of the multivariate regression that includes *Treat×Post* and the control variables. The treatment indicator variable, *Treat*, equals 1 (0) if a firm is located within (more than) 1 kilometer radius of an operational 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 points, with detailed definitions provided in Appendix Table A3. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure A1: Subway construction in China



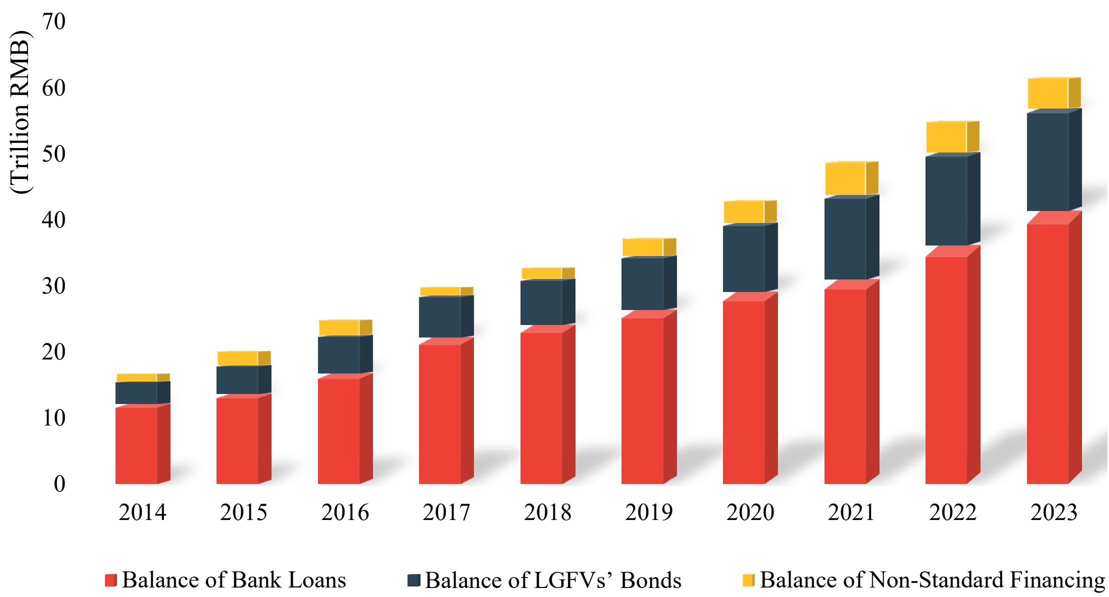
Notes: This figure illustrates the development of China's subway system over time. The left panel plots the number of cities with operational subway systems (left axis) and total subway ridership in billions of passengers (right axis) from 2000 to 2024.The right panel shows the growth of the number of subway lines (left axis), stations, and total operating length in kilometers (right axis) over the same period. 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)



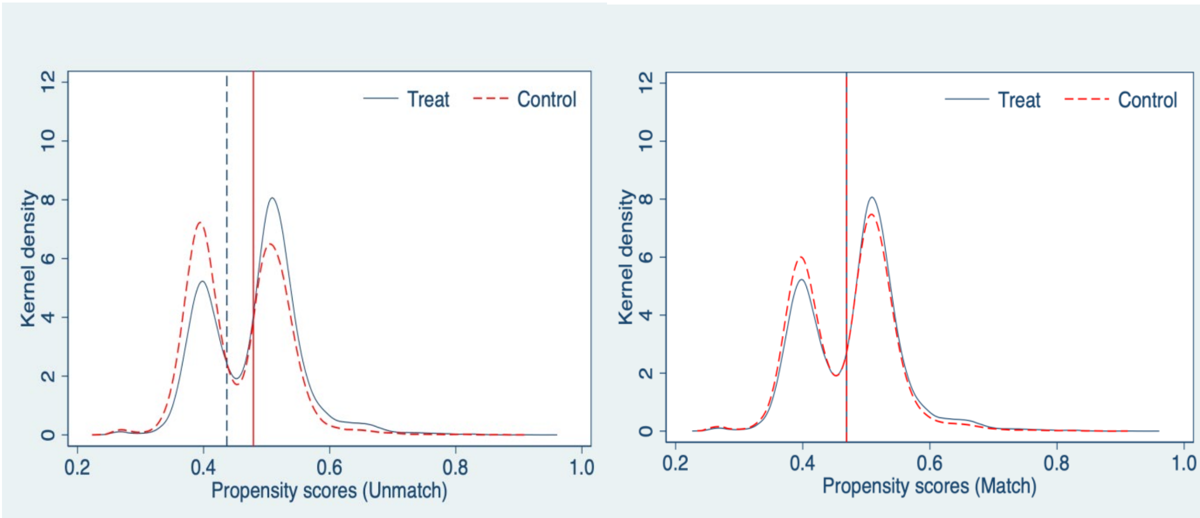
Notes: This figure presents the spatial relationship based on a representative travel time of each transport mode. The figure focuses on two subway stations in Beijing, i.e., Dawang Road and Fuxingmen, located roughly 15 kilometers apart. The comparison covers five transport modes: (i) subway (34 minutes), (ii) private car (38 minutes), (iii) walking (2 hours 58 minutes), (iv) bus (3 hours 25 minutes), and (v) e-bike (51 minutes). Travel time is estimated on Apple Maps as of August 2025, 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 (more than) a 1 kilometer radius of an operational 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 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.