Mortgages, Subways and Automobiles

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Abstract

We examine the impact of subway expansions on mortgage repayment behavior in Delhi, India. Using administrative data from one of India's largest mortgage lenders, we estimate that households in postal codes with newly opened stations experience a 4.42% decrease in mortgage delinquencies and a 1.38% increase in prepayments. These improvements are attributed to households' reduced reliance on automobiles. Vehicle registration records show a 1.2% decline in the market share of four-wheelers, accompanied by a 6.5% drop in vehicle spending. Financially constrained households benefit the most, reducing purchases of low-quality vehicles and showing the largest improvements in mortgage repayment performance

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1 Introduction

Cities worldwide are expanding urban subway networks to reduce transportation-related greenhouse gas emissions (Axsen et al. (2020)). As governments prioritize these investments, quantifying their societal impact becomes a first order concern. Recent studies have highlighted subways' direct benefits, such as reduced commuting costs (Gupta et al. (2022)), decreased traffic congestion (Yang et al. (2018); Anderson (2014)), and improved air quality (Gendron-Carrier et al. (2022); Chen and Whalley (2012)). Subways have also been found to generate spillover effects, such as fostering innovation (Koh et al. (2022)) and firm-level productivity (Chen and Wu (2024)). However, fully capturing the benefits that subways provide is challenging because many impacts are hard to measure and unfold over the long term (Glaeser and Poterba (2020)). In this paper, we contribute to this discussion by examining how subway expansions in Delhi, India, can enhance household financial well-being through mortgage repayment and automobile purchases.

The Delhi Metro, one of the world's largest and busiest subway systems, is widely recognized as a milestone in sustainable urban development. In 2011, it became the first subway system certified by the United Nations to earn carbon credits, reducing greenhouse gas emissions by 630,000 tonnes annually. While its effectiveness in managing rapid urban growth and alleviating traffic congestion is well-documented (Goel and Gupta (2017)), the Metro also has the potential to challenge the perception that sustainability initiatives inevitably impose financial burdens on households. This study demonstrates that sustainable infrastructure investments, like the Metro, can deliver measurable financial benefits to households, highlighting their dual role in promoting both environmental and economic well-being. Focusing on mortgage repayment—the largest financial liability on household balance sheets—we find that improved access to public transportation, by reducing reliance on automobiles, can ease financial pressures and enhance mortgage repayment rates. This also has significant implications for inequality: lower-income households, more likely to replace automobile use with subway access, stand to benefit most, while higher-income households are less impacted. Thus, we can examine whether infrastructure investments can promote financial equity by providing relief to financially constrained households through lower transportation costs.

Despite its importance, we know little about the direct relationship between subway access and mortgage repayments. Similarly, the link between subway access and vehicle purchases is not well understood. A key challenge in studying these relationships is identification: various factors—such as income fluctuations, job relocations, and macroeconomic conditions—can influence mortgage repayment decisions, making it difficult to isolate the direct effect of subway access. Our setting in Delhi helps address this issue, as the phased expansion of the Delhi Metro creates a quasi-natural experiment. To account for heterogeneity in transportation costs and vehicle ownership across households, we also need a setting that offers variation in automobile types and their associated expenses. Delhi's diverse vehicle landscape—including two-wheelers, three-wheelers, and four-wheelers at various price points—makes it an ideal context for our study.

Another challenge is data availability. To overcome this, we utilize two key datasets which allow us to match individual home addresses to the timing of subway expansion. The first is a unique administrative dataset from a major Indian mortgage lender, spanning from April 2015 to February 2020. It contains comprehensive records of properties—including locations and values—and detailed information on households' monthly mortgage payments and borrower profiles such as income levels and employment. The second dataset relates to vehicle registration records provided by the Ministry of Road Transport and Highways, with detailed information of the type of vehicle being purchased. By combining these datasets, we can identify how subway expansions reduce vehicle expenditures and enhance household financial stability. While the mortgage lender data shows changes in repayment, the vehicle registration data demonstrates how reduced reliance on automobiles translates into greater financial flexibility.

Using the administrative data from the mortgage lender, we begin by investigating the impact of subway access on households' mortgage repayment behavior. Our key outcome variable is the delinquency or prepayment amount, defined as the difference between cumulative installments and repayments. We classify a borrower as delinquent when the balance turns negative and as prepaid when it turns positive.[1] Formally, we estimate the effects of subway expansions on monthly mortgage delinquency and prepayment using a difference-in-differences research design. This method compares households in postal codes where new subway stations have recently opened (treatment group) to those in other areas of Delhi (control group). Since subway station openings occur at different times, we employ staggered treatment periods in our analysis. Building on recent studies (Baker et al. (2022)), we address potential biases from treatment effect heterogeneity using a stacked difference-in-differences model, which is widely adopted for its flexibility in handling variation in treatment timing and its computational efficiency.

Our empirical estimates show that subway expansions do reduce mortgage delinquency. For households in the same postal code as the new subway station, we find that the delinquency rate decreases by 4.42%, while delinquent amounts by 39.2%. However, this reduction is not immediate. According to our difference-in-differences event study, the reduction starts three months after the subway station opens and remains stable for up to 10 months. In contrast, subway expansions lead to a 1.38% increase in

[1] This definition is standard in the literature; see Jiang et al. (2014) and Gallagher et al. (2019). Mortgage prepayment refers to borrowers paying ahead on their payments. We exclude prepayments due to home sale and default, as discussed in Gerardi et al. (2023).

prepayment rates. Unlike the delayed response seen with delinquency, our event study shows an immediate rise in the prepayment rate during the month of subway expansions. This lasts for only 3 months. As a result, while there is an initial increase in prepayment amounts in the first 3 months following subway expansions, the average impact on prepayment amounts remains positive but statistically insignificant 10 months after the station's opening.

To reinforce our findings, we then consider the proximity to subway stations. Specifically, we examine how the effects vary with distance by subdividing the control group into areas with postal codes that are near to and far from the treatment areas. This approach allows us to assess whether the impact of subway access decreases as the distance from the station increases. Indeed, our findings show that the positive impacts on the treatment group are more pronounced relative to control groups located further away from subway stations. In other words, among households residing outside the postal code area of a new subway station, those situated closer to the station exhibit significantly lower delinquency rates and higher prepayment rates as compared to those households located further away. This gradient or "distance-decay" effect indicates that the benefits of subway access on mortgage repayment behavior extend beyond the immediate vicinity of the stations but diminish with increasing distance.

We now turn to the underlying mechanisms driving our results. In order to test whether the observed effects are attributable to changes in automobile expenditures, we utilize government vehicle registration data. This rich dataset provides comprehensive information on all automobile transactions in Delhi during the same period as our mortgage data, including registration dates, vehicle types, prices, and ownership details. By analyzing this data, we aim to explore how the opening of new subway stations impacts private vehicle ownership patterns. To examine whether improved public transportation access reduces the reliance on private vehicles, we employ regression models consistent with our earlier baseline analysis. The central hypothesis is that as households benefit from better public transit options, their need for private vehicle ownership—and the associated financial burdens—diminishes, freeing up disposable income that can be redirected toward mortgage repayments, ultimately enhancing financial well-being.

Our empirical findings corroborate this hypothesis. We first analyze vehicle choices. In examining approximately 3 million registration records, we find that subway expansions reduce the likelihood of a registered vehicle being a four-wheeler by 0.4%. Aggregating the data at the postal code level reveals a further 1.2% decline in the market share of four-wheelers. This suggests that households are opting for cheaper two-wheelers over four-wheelers, reflecting a shift in transportation preferences driven by improved public transit availability. Next, we assess the absolute numbers within each vehicle category. While the market share of four-wheelers is declining, both categories are experiencing reductions. Specifically, we observe an overall decrease of 7 units in four-wheelers and a 2-unit decrease in two- and three-wheelers. Moreover, total automobile spending at the postal code level decreases by 6.5%, and average spending per vehicle falls by 4.7% after the opening of new subway stations. This reduction in vehicle expenditures suggests that households are reallocating funds away from private vehicle ownership, allowing for more available funds for mortgage payments and easing financial constraints.

The impact of subway expansions is likely to be more pronounced among financially constrained or lower-income households, as they are more sensitive to changes in transportation costs than wealthier households. While we lack direct income data for automobile buyers, we examine this effect by distinguishing between high- and low-quality vehicle purchases as a proxy for household income.[2] We posit that households purchasing low-quality four-wheelers are more likely to be lower-income and financially constrained. Indeed, our results show that after subway expansions, the number of low-quality four-wheelers declines by 9 units, suggesting that financially constrained households are opting out of purchasing these vehicles. In contrast, there is an increase in high-quality four-wheelers by 2 units, which are likely purchased by higher-income households who do not need additional liquidity. By reducing expenditures associated with private vehicle ownership, we find that the financial well-being of those who purchase lower-quality four-wheelers could be improved, as they spend less on automobile purchases and associated costs such as fuel and maintenance.

To further validate our hypothesis, we strengthen the connection between the vehicle and mortgage datasets by analyzing the heterogeneous effects of subway expansions based on the initial income levels of mortgage applicants. Our results reveal that lower-middle-income households benefit the most from subway expansions. They experience a greater reduction in delinquency rates and amounts compared to higher-income households, while also showing a more substantial increase in prepayment rates and amounts. In contrast, the lowest-income households exhibit no significant changes in delinquency or prepayment behavior. A likely explanation is that these households may have been unable to afford private vehicles before the expansions, limiting the potential impact of reduced transportation costs.

In sum, our findings provide strong evidence that improved public transportation infrastructure enhances household financial well-being by reducing vehicle expenditures. Since vehicle costs are a major driver of household debt, our analysis extends the existing literature that links liquidity constraints to higher mortgage defaults (e.g., Ganong and Noel (2020), Ganong and Noel (2023)) and lower prepayment rates (e.g., Amromin et al.

[2] We categorized vehicles into high- and low-quality groups based on their prices relative to the average vehicle price. Vehicles priced below the average are classified as low quality, while those priced above are considered high quality.

(2007)). We contribute to this research by showing that infrastructure improvements, such as subway expansions, can alleviate liquidity constraints and improve mortgage repayment behavior among financially constrained households, who can substitute private vehicle use with public transportation.

We also consider several alternative explanations. While there could be other factors—such as increased income or improved macroeconomic conditions—that might account for our findings, we find no evidence supporting these explanations. First, we examine the potential income effect. It is plausible that subway expansions could enhance labor productivity and workforce participation, leading to higher incomes and improved mortgage performance. To test the productivity channel, we compared outcomes between public and private sector workers. Since public sector workers generally have fixed incomes, we would expect private sector workers to benefit more if productivity had improved. We also examined the labor participation channel by analyzing gender differences in response to subway expansions. The idea is that if commuting becomes easier, women who usually have more time constraints in commuting (Farré et al. (2023)) may work more or join the workforce, thereby reducing their mortgage delinquency or increasing prepayments. However, our analysis revealed no significant differences between these groups, rejecting both the productivity and labor participation hypotheses. Furthermore, we found no direct evidence that individuals' incomes increased following the subway expansion.

An alternative explanation is that subway expansions boost economic conditions. To test this, we examine the effects of new subway stations on housing values and loan amounts. However, our findings show no evidence of increases in these indicators following subway expansions. We also explore the housing price channel by analyzing loan-to-value (LTV) ratios. Higher housing prices reduce the probability of negative equity, leading to fewer strategic defaults. Borrowers with higher LTV ratios are more exposed to this risk, so if our results were driven by property value increases, we would expect them to become less delinquent. Nonetheless, we find no such reduction in delinquency among high-LTV borrowers, indicating that increased property values from better transit access did not mitigate mortgage risks. Our results align with recent studies such as Severen (2023), which finds subways have limited effects on local productivity and the housing market. Last, to ensure the robustness of our findings, we perform several additional checks, including the use of alternative fixed effects, placebo tests, different data transformations, and sub-sample analyses. All these tests confirm the validity of our results.

Our findings carry important policy implications as governments focus on sustainable transport infrastructure development. While sustainability initiatives can bring short-term financial pressures like higher taxes and energy costs, our research shows they can also deliver financial benefits. By lowering transportation costs and freeing up funds, subway expansions support better mortgage repayment, revealing an overlooked advantage of sustainable infrastructure. Neglecting these spillover effects will underestimate the full economic value of subway infrastructure. Our back-of-the-envelope estimates suggest that by reducing delinquency, new subway stations could lower mortgage default rates by 0.08%. Thus, a reduction in defaults not only strengthens household balance sheets but also contributes to financial sector stability, supporting long-term economic growth. These findings suggest that transit infrastructure investments should be viewed as both environmental and financial interventions, with the potential to enhance economic resilience and inclusion.

1.1 Related Literature

This paper contributes to several strands of literature. First, it adds to the literature on the effects of subways. Previous studies have shown that subways can reduce air pollution (Chen and Whalley (2012); Gendron-Carrier et al. (2022); Li et al. (2019)), road congestion (Gu et al. (2021); Yang et al. (2018); Anderson (2014)), and commuting costs (Severen (2023); Gupta et al. (2022)) in different cities. There could also be higher firm-level productivity (Chen and Wu (2024)). On the other hand, the growing investment in subway networks may have negative spillover effects including increases in urban inequality (Lee and Tan (2024)) and coronavirus infection (Harris (2020)). In terms of housing, much attention has been given to the role of urban transport in property value appreciation (e.g., Zheng et al. (2016)). Here, we focus on mortgages, a relatively unexplored area. Our paper adds to the literature by focusing on the effects on households' mortgage repayment decisions. By documenting the spillover effects of subway expansions in improving households' financial flexibility through decreased auto purchases, we highlight a previously unexplored mechanism.

Next, this study is related to the literature on mortgage delinquency. While studies have highlighted the role of income falsification (Jiang et al. (2014)), immigrants (Lin et al. (2016)), health insurance (Gallagher et al. (2019)), and house price (Haughwout et al. (2008)) on mortgage delinquency, liquidity shocks have often been cited to play a key role in mortgage delinquency. Kaufmann et al. (2011) suggest that higher household energy expenditures raise mortgage delinquency rates based on a cointegrating vector autoregressive (CVAR) model. Based on the National Mortgage Database and the American Survey of Mortgage Borrowers, Low (2023) highlights ten types of liquidity shocks as the primary triggers for mortgage default. Similarly, Ganong and Noel (2023) show that 70 percent of mortgage defaults are driven solely by cash-flow shocks. This paper contributes to the growing body of research emphasizing the role of financial constraints in mortgage delinquency. By connecting delinquency with vehicle purchases after subway expansions, we provide an additional channel through which vehicle expenditures can influence mortgage delinquency.

Finally, we contribute to the literature on mortgage prepayment. Unlike mortgage delinquency, relatively little work has been done on the factors that influence mortgage prepayment. Existing papers focus on the effects of monetary policy (Berger et al. (2021); Gerardi et al. (2023)) and liquidity constraints (Amromin et al. (2007)) on mortgage prepayment. While a higher mortgage prepayment rate could imply a lower delinquency rate and the factors influencing prepayment and delinquency could be highly similar, there is little work connecting them directly. Scharlemann and Shore (2022) identify the causal effect of increasing mortgage interest rates on default, delinquency, and prepayment using the evidence of Home Affordable Modification Program (HAMP) reset. They find that increasing mortgage rate leads to higher default and delinquency, while prepayments stay relatively rare as the incentive to refinance remains muted. Our paper contributes to the literature on prepayment by highlighting the role of vehicle expenditures on mortgage prepayment instead of focusing on monetary policy. Importantly, this paper establishes a connection between mortgage delinquency and prepayment by documenting the contrasting effects of subway expansions on these two aspects.

The remainder of the paper is organized as follows. Section 2 introduces the background about subway expansions in Delhi and describes the data used in this paper. In Section 3, we present our main empirical analyses on mortgage delinquency and prepayment. Section 4 examines the role of automobile purchases and provides additional evidence of income. Section 5 tests for other channels, conducts several robustness checks, and presents a simple back-of-the-envelope exercise to quantify the benefit of fewer delinquency. Finally, Section 6 concludes.

2 Background

2.1 Subway Expansions in Delhi

Delhi, the capital city of India, has a population exceeding 33 million as of 2024. This places it comparable in size to countries like Peru and Malaysia, while surpassing the populations of nations such as Australia and the Netherlands. In India, the Delhi Metro is the largest and busiest subway rail system, operating over 3,000 trips daily and carrying approximately 2.5 million passengers. The Delhi Metro also features interchanges with the Rapid Metro Gurgaon and Noida Metro, enhancing connectivity across the region. It is managed by the Delhi Metro Rail Corporation, which is jointly owned by the governments of India and Delhi. It commenced operations on 25 December 2002 and has since undergone several expansions. To date, phases 1, 2, and 3 were completed in 2006, 2011, and 2021, respectively. These development phases represent major milestones, providing Delhi and the National Capital Region with a reliable, efficient transportation system.

The impact of the Delhi Metro has been well-recognized. It has helped to ease the immense pressure on Delhi's road networks, reducing traffic congestion and the travel time for commuters (Jain et al. (2014)). Moreover, the expansion of the metro network has been pivotal in tackling the city's growing environmental issues, such as air pollution and greenhouse gas emissions. By offering an attractive alternative to private vehicles, the Metro has played a key role in lowering vehicular emissions, directly addressing the critical problem of deteriorating air quality (Goel and Gupta (2017)). Globally, the Delhi Metro's impact on reducing greenhouse gas emissions has been recognized through carbon credits awarded under the Kyoto Protocol's Clean Development Mechanism (CDM). This distinction underscores the Metro's critical role in advancing sustainable urban transport and addressing environmental challenges.

In our study, we focus on the expansion of subway stations in the Delhi Metro between 2015 and 2019. This period captures the majority of station openings during Phase 3 of the expansion, which introduced new subway stations in 41 different postal code areas across Delhi. A postal code in India consists of a six-digit numeric code used by the Indian Postal system. In total, there are 100 postal codes in Delhi, ranging from 110000 to 110099. On average, each postal code covers an area with a radius of approximately 2.18 km. Figure 1 shows the evolution of subway stations in Delhi from 2015 to 2019. The blue circles represent subway stations that existed up to 2014, while the red circles indicate new subway lines constructed between 2015 and 2019. Grey circles denote stations built either outside of Delhi or after 2019.

< Insert Figure 1 here >

Phase 3 of the Delhi Metro expansion aimed to extend the metro's reach and improve connectivity within Delhi and its growing suburbs. This phase added over 160 kilometers of new lines, including the Magenta, Pink, and Grey Lines, along with extensions to the Blue, Pink, Magenta, and Violet Lines. The project also integrated the Rapid Metro Link in Gurugram, enhancing transit options between Delhi and its satellite cities. By offering a sustainable alternative to road travel, Phase 3 addressed Delhi's increasing transportation demands. It improved access to underserved areas, making commuting more efficient for millions of residents. This expansion was a key step in the city's efforts to develop a modern transit system that reduces pollution and eases traffic congestion. Beyond improved connectivity, the Metro has the potential to enhance residents' quality of life in various ways. Given these developments, it is of interest to examine how subway station openings between 2015 and 2019 during Phase 3 impacted household finances.

2.2 Mortgage Data

To examine the impact of subway expansions on household financial well-being, we use a combination of two datasets. The first is mortgage data from one of India's largest mortgage lenders, which holds over 20 percent of the market share in India and is representative across all states. This rich administrative dataset contains detailed information on borrowers, loan types, and mortgage repayments. For each mortgage applicant, we have demographic data such as gender, age, occupation, and annual income. For the loans, we have information of loan tenure, interest rate type (fixed or floating), property value at purchase, loan amount, borrower address, and property postal code. Importantly for our analysis, the dataset includes panel-level information on monthly repayments, such as the installment start date and the amount of each monthly payment.

Our dataset begins in April 2015, coinciding with the start of Phase 3 of the Delhi Metro expansion.[3] We exclude data from March 2020 onwards due to the onset of the coronavirus pandemic, which led to lockdowns and shifting commuting patterns as more people began working from home. For the period between April 2015 and February 2020, we track monthly indicators for delinquency and prepayment, as well as the corresponding amounts for each mortgage applicant. Formally, loan delinquency occurs when a borrower fails to make timely payments in accordance with the terms of the loan agreement. In our dataset, borrowers are considered delinquent if they fall behind on mortgage payments, and the delinquency amount is defined as the cumulative installments owed minus the total amount paid. Conversely, mortgage prepayment refers to paying off a loan before the scheduled maturity date. Prepayment includes making extra payments, exceeding the required monthly installment, or fully repaying the remaining loan balance in a lump sum. Borrowers are deemed to have prepaid if their account balances exceed zero at the end of the month. Similar to delinquency, the prepayment amount is measured as the total repayment minus the cumulative installment amount.[4]

When constructing our main sample, we focus on the group of households who purchase their properties before the expansions of the subway. This is to reduce the possibility of selection bias that may occur if individuals purchase houses due to their preference for such transit option. Table 1 presents the summary statistics, including the number of observations, the means, and the standard deviations of the full sample, the control sample, and the treated sample from April 2015 to February 2020. In all, we have 9,681 households in our sample, with 45 percent of them being in the treatment group and 55 percent of them in the control group.

[3] The initial set of stations in our study began operations in June 2015, while the last group of stations opened in October 2019.

[4] Since both delinquency amount and prepayment amount are cumulative, it is possible to see a large number of them. Additionally, prepayment amount could be much larger than delinquency amount as borrowers are likely to prepay entire remaining balance.

< Insert Table 1 here >

There are several key observations regarding the monthly installment payments. On average, monthly installments amount to ₹24,271.[5] In addition, the data reveal a high delinquency rate, with 29% of borrowers falling behind on their payments each month.[6] When we compare the treatment and control groups, we observe a slightly higher delinquency rate in the control group (30%) compared to the treatment group (28%). However, the delinquency amounts tell a different story: the average delinquency amount in the control group is lower than that of the treatment group. This difference is likely driven by the large variation in payment behaviors, as evidenced by the much higher standard deviation in the treatment group—more than three times larger than that of the control group. Despite the high delinquency rate, the prepayment rate is also high. The overall monthly prepayment rate stands at 60%. Thus, a rough interpretation of our summary statistics suggests that 29% of borrowers are delinquent, 60% are prepaying, and only 11% are right on track.

Table 1 also reports the main time-invariant mortgage and demographic characteristics. The proportion of mortgage with fixed interest rate is 14% within the full sample, and the average loan tenure is 7,632 days (about 21 years). The loan to value ratio is measured as the ratio of the total mortgage amount to the appraised value of the property. The average LTV ratio in our sample is 56%. Regarding demographic characteristics, 69% of individuals in our sample are male. The average age of mortgage applicants is 49 years, and 65% are employed in the private sector. Data on annual income is more limited, with only 6,761 observations, and the average annual income is ₹413,053. On average, the variables between the treatment and control group are close to one another.

2.3 Vehicle Registration Data

The second dataset utilized in our analysis is the vehicle registration data, provided by the Ministry of Road Transport and Highways in India. This dataset comprises over 3 million records of vehicle registrations in Delhi, spanning from April 2015 to February 2020. The data includes detailed information such as the registration date, the district-level Regional Transport Office (RTO) where the vehicle is registered, the vehicle manufacturer, body type, price, and vehicle category. Table 2 provides the summary statistics, presenting the number of observations, mean values, and standard deviations for the entire sample, as well as for the control and treated samples, during the specified period.

[5] Note that ₹ refers to the symbol of the Indian rupee. Based on the exchange rate on February 2020, ₹24,271 is equivalent to around 340 US dollars.

[6] This is larger in magnitude than the 19% home delinquency rate reported by Gallagher et al. (2019) in the U.S. market.

< Insert Table 2 here >

According to Table 2 Panel A, 74% of vehicle registrations in Delhi are for two- and three-wheelers, while four-wheelers account for the remaining 26%. Since both two-wheelers and three-wheelers are primarily used for short-distance commuting in Delhi, we group them together for our analysis. The average price of two- and three-wheelers is ₹68,376, considerably lower than the average price of four-wheelers which stands at ₹840,663.[7] The distribution of automobile types is relatively similar between the control and treatment groups. In the control group, 75% of registered vehicles are two- and three-wheelers, compared to 74% in the treated areas. The average price of two- and three-wheelers is ₹66,246 in the control group, compared to ₹70,255 in the treatment group. For four-wheelers, the average price is ₹813,157 in the control group, slightly lower than ₹863,521 in the treatment group.

Next, we aggregate our data at the postal code level. Table 2 Panel B presents the descriptive statistics. On average, 415 two- and three-wheelers and 143 four-wheelers are sold in each postal code area. We note that households in areas with subway stations purchase more vehicles on average relative to those in control areas. In the control group, an average of 337 two- and three-wheelers are registered each month, compared to 512 in the treatment group. Similarly, the treatment group registers more four-wheelers on average (184) than the control group (112). While different factors like population or income differences could explain some of these variations, they do not undermine the suitability of these groups in our analysis, as our focus is on changes in vehicle registration.

We further categorize the automobiles into high-quality and low-quality based on whether their prices are above or below the mean within each category. This follows existing literature, such as Bai et al. (2020), which shows that the quality of an automobile is strongly correlated with its price. Overall, there are 85 high-quality and 330 low-quality two- and three-wheelers. In contrast, the average number of four-wheelers is 41 high-quality and 102 low-quality units. We then examine the distribution between the control and treatment groups. In control areas, 70 out of 337 two- and three-wheelers sold are high-quality, compared to 106 out of 512 in the treated areas. Similarly, 31 out of 112 four-wheelers in control areas are high-quality, versus 55 out of 184 in the treated areas. We also analyze average and total spending on vehicles, presenting these figures in logarithmic form, and find that spending levels are similar between control and treatment groups at the postal code level.

[7] Based on the exchange rate on February 2020, ₹68,376 is equivalent to around 957.3 US dollars. ₹840,663 is equivalent to about 11,769.3 US dollars.

3 Effects of Subway Expansions on Mortgage Repayments

The main objective of this paper is to study the effects of subway expansions on mortgage delinquency and prepayment in Delhi. Specifically, we aim to address two key questions: first, whether the introduction of subway stations affects households' monthly delinquency rates and delinquency amounts; second, whether the expansions lead to an increase in mortgage prepayments. Similar to Koh et al. (2022), our focus is on subway extensions rather than the initial opening of subway lines. The advantage of examining extensions is that these stations are more likely to serve as linking hubs, making their selection somewhat random, which helps us mitigate potential endogeneity bias.

As discussed in section 2.1, the phased expansions of the Delhi Metro offer a quasi-experimental setting to assess their impact on households. However, the staggered opening of new subway stations divides the sample into already-treated, not-yet-treated, and never-treated groups. A key concern with staggered difference-in-differences (DiD) is the potential for biased comparisons between late- and early-treated units, which can distort Two-Way Fixed Effects (TWFE) estimates when treatment effects vary across cohorts (Baker et al. (2022)). Given the variation in station sizes and locations across expansion areas, treatment effects are likely to be heterogeneous, increasing the risk of bias in TWFE estimates. To address this issue, we apply a stacked DiD model, which has gained traction in recent studies (e.g., Deshpande and Li (2019), Cengiz et al. (2019)).[8] This approach constructs event-specific datasets that include all treated observations within a cohort and all never-treated units within the treatment window. Treatment effects are estimated within each cohort and then combined using variance-weighted averages across cohorts.

3.1 Baseline Specification

Formally, we estimate the impact of subway expansions on household mortgage delinquency and prepayment using a stacked difference-in-differences (DiD) model, based on subway station openings in 41 postal code areas in Delhi. Our baseline control group consists of the remaining 59 postal code areas where no subway stations opened between 2015 and 2019. Thus, each of the 41 stacks in the DiD model compares the monthly changes in mortgage delinquency and prepayment in treated postal code areas before and after subway expansions with the corresponding changes in the control areas. The

[8] As noted by Baker et al. (2022), the stacked DiD model is more efficient and easier to implement compared to alternatives such as those proposed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021).

regression specification is as follows:

$$Y_{ijm} = \sum_{m=\underline{m}, m\neq -1}^{\bar{m}} \beta_m \cdot Treated_{im} \cdot d_{jm} + \mu_{ij} + \lambda_{jm} + \varepsilon_{ijm} \tag{1}$$

where dependent variable Y_{ijm} includes the indicator for delinquency, log delinquency amount, indicator for prepayment, and log prepayment amount of household i in stack j and on month m. The treatment dummy $Treated_{im}$ indicates the treatment status for households. d_{jm} is a dummy variable that equals 1 if an observation in cohort j is m months away from the opening of the new subway station, with $m = 0$ representing the month of opening. $[\underline{m}, \bar{m}]$ refer to time horizons included in the sample, where $\underline{m} = -5$ and $\bar{m} = 10$.[9] Our baseline specification controls for individual-by-stack fixed effect μ_{ij} and month-by-stack fixed effect λ_{jm}. ε_{ijm} is the error term. Standard errors are clustered by postal code, the level at which treatment is assigned.

The month prior to the expansions, $m = -1$, serves as the reference point. Here, the coefficient β_m represents variance-weighted treatment effects across all cohorts. When the dependent variable is an indicator for delinquency or prepayment, $m \geq 0$ (< 0) reflects the probability change in delinquency or prepayment in month m after (before) subway expansions, relative to the month preceding the expansion. If the dependent variable is the logarithm of delinquency or prepayment amounts, the coefficient captures the monthly percentage change in these amounts after (before) the expansions. Thus, this can be interpreted as an event study analysis, testing for pre-trends when $m < 0$, and the persistence of effects when $m \geq 0$.

To estimate the average effects of subway expansions on delinquency and prepayment, we modify the dynamic specification as in Equation (1) to the following specification:

$$Y_{ijm} = \beta \cdot Treated_{im} \cdot Post_{jm} + \mu_{ij} + \lambda_{jm} + \varepsilon_{ijm} \tag{2}$$

where $Post_{jm}$ is a dummy variable that equals 1 for all time periods after the opening of subway stations in cohort j. Here, β refers to the average changes of dependent variables as a result of subway expansions.

We start by analyzing the impact of subway expansions on delinquency rates. Column (1) of Table 3 reports the average effect of these expansions on the probability of households falling into monthly delinquency, as estimated from Equation (2). Based on our stacked Difference-in-Differences (DiD) estimation, the results show that subway expansions do reduce the monthly delinquency rate, with an average decrease of 4.42%

[9] There are 3 subway stations opened on October 2019 but our data ends on February 2020, which means we can only estimate post-treatment effects of them up to $\bar{m} = 4$. But we can estimate the full impacts for the opening of other subway stations.

(significant at the 1% level). This indicates that improved access to public transit may contribute to reducing financial distress for households.

< Insert Table 3 here >

In order to validate the parallel-trends assumption underlying our stacked DiD specification, we examine the dynamic effect of subway expansions on the delinquency rate over a period spanning 5 months before and 10 months after the station opening. Panel A of Figure 2 presents the month-by-month estimates, alongside the corresponding 95% confidence intervals based on the regression model outlined in Equation (1). The results show no evidence of diverging pre-treatment trends, supporting the validity of the parallel-trends assumption. Importantly, we observe that the delinquency rate remains relatively stable before the station openings and does not begin to decrease until the third month after the expansions. This decline continues steadily over the first six months, reaching its lowest point around the seventh month, where it stabilizes at approximately 4%. The sustained reduction in delinquency rates indicates a significant and lasting impact of subway expansions, with the effect becoming particularly evident by the 10-month mark.

< Insert Figure 2 here >

Next, we focus on the monthly delinquency amount. Column (2) of Table 3 shows that subway expansions leads to a 39.2% reduction in monthly delinquency amount (significant at the 1% level). Panel B of Figure 2 illustrates the dynamic effects of subway expansions on delinquency amounts. As with previous findings, there is no evidence of pre-treatment trends. The pattern of delinquency amount dynamics is similar to that of delinquency rate: it begins to decline three months after a station opens and continues to decrease over the next six months. The reduction reaches its lowest point, stabilizing at around 35%, between the sixth and ninth months. The impact of the subway expansions persists for more than 10 months.

We now turn to prepayment rates. Based on Column (3) of Table 3, we note that households' monthly prepayment rate increases by 1.38% (significant at the 5% level) after the expansions on average. The dynamic effect in Panel C of Figure 2 does not show evidence of pre-trends before treatment. Different from the response of delinquency, prepayment rate increases immediately on the month of subway expansions. The increments in prepayment rate last for three months. After a dip on the fourth month, the positive effect of the expansions holds significant until 6th month. Interestingly, the immediate increase in prepayment rates suggests that households may prioritize reducing their debt burdens in response to improved transportation access. This shift could reflect a broader financial adjustment, as households allocate more resources toward prepaying existing loans following subway expansion.

Finally, we analyze the monthly prepayment amount. Column (4) of Table 3 reports a 10% increase in prepayment amounts following subway expansions, though this effect is not statistically significant at the 10% level. However, as shown in Panel D of Figure 2, the dynamic effects of prepayment amounts resemble those of prepayment rates. While the aggregate effect of subway expansions on monthly prepayment amounts is not statistically significant, we observe statistically significant increases during the first three months post-expansion. These effects diminish over time, which explains the lack of statistical significance in the overall results. Taken together, our findings suggest that subway expansions reduce households' monthly delinquency rates, lower delinquency amounts, and lead to an increase in monthly prepayment rates, even if the effect on prepayment amounts is more short-lived.

3.2 Different Control Groups by Distance

In what follows, we analyze the heterogeneous effects of subway expansions based on the distance from households to the nearest subway station. Our underlying hypothesis is that the impact of subway access diminishes as distance from the station increases. While we centre our analysis on households within the same postal code as the station, it is likely that proximity plays a role too. Households located closer to the station should experience stronger effects relative to those farther away. Furthermore, subway stations located near postal code boundaries can create spillover effects, as households in adjacent postal codes might actually be closer to the station than some within the designated area.

To test this hypothesis, we vary the control groups in two ways, while keeping the treatment group unchanged. First, the control group is selected from postal code areas without subway expansions during the sample period but are geographically close to the treatment areas. This includes 29 neighboring areas whose postal code numbers are adjacent to the postal code numbers of the treatment areas. Second, we consider another set of control groups, consisting of the remaining 30 distant postal code areas without subway expansions. This method is similar to the "donut" approach used in existing studies (Barreca et al. (2011)). In our case, the observations close to the areas with subway expansions are removed. Subsequently, we re-run Equations (1) and (2) based on the new control groups, and present them in Table 4 and Figure A.1 respectively.

< Insert Table 4 here >

We begin by examining the results using neighboring postal code areas as the control group. As shown in Table 4 Panel A, the delinquency rate decreases by 2.5% (significant at the 5% level), and the delinquency amount drops by 25.7% (significant at the 1% level) following subway expansions. These effects are clearly smaller in magnitude compared to the baseline results. Furthermore, the impacts on prepayment rates and amounts become statistically insignificant. This is supported by Figure A.1, which illustrates that the dynamic effects on both delinquency and prepayment lose significance relative to the results with the unrestricted control group. This attenuation can be explained by the fact that individuals in neighboring postal code areas also have relatively easy access to subway stations, given the limited size of each postal code area.

In Table 4 Panel B, we turn our attention to using areas farther from subway stations as the control group. Compared to households living far from the new stations, those sharing the same postal code as the station experience a 5.72% reduction in delinquency rates (significant at the 1% level) and a 48.7% drop in delinquency amounts (significant at the 1% level). Additionally, their prepayment rate rises by 1.93% (significant at the 5% level) following subway expansions. While the average increase in prepayment amount remains statistically insignificant, the effects are evidently more pronounced when using distant areas as the control group. As shown in Figure A.2, the dynamic effects on delinquency and prepayment are slightly larger than in the baseline results. Our results underscore that proximity to subway stations is a critical factor in shaping households' mortgage behavior, with the impact tapering off as distance increases. This reinforces our conclusion that subway expansions influence mortgage decisions, and households closer to new stations benefit more, highlighting the broader positive spillover effects of improved transit access.

4 Role of Automobile Purchases

We have demonstrated that the opening of a subway station near a household's property influences both mortgage delinquency and prepayment decisions. A key mechanism driving this effect is the reduction in transportation costs, which may allow households to either prepay mortgages or lower their delinquency risk. In this section, we explore the impact of subway expansions on automobile purchases, using these purchases as a proxy for improved liquidity. By analyzing changes in household vehicle-buying behavior, we assess the extent to which households substitute private vehicle use for subway transportation and how this transition affects their overall financial outcomes. Furthermore, we investigate whether these effects differ by income level, particularly between lower- and higher-income households. This allows us to better understand how enhanced transit access helps ease financial constraints across different income groups. In doing so, we aim to establish a clear connection between subway expansions, reduced vehicle expenditures, and enhanced mortgage performance.

4.1 Effects of Subway Expansions on Automobile Purchases

Why do households become less delinquent and increase prepayments when a subway station opens nearby? It is plausible that financially constrained households shift from private vehicle use to the more affordable subway system, generating savings in transportation costs. By cutting down on expenses associated with car ownership—such as loan payments, fuel, maintenance, and insurance—households are able to improve their financial position. This reduction in financial burden then provides borrowers with additional resources to allocate towards their mortgage obligations. Therefore, improved liquidity from reduced transportation cost allows them to better manage mortgage payments and, in many cases, make early prepayments.

To examine the effect of subway stations expansions on automobile purchases in Delhi, we begin by studying households' likelihood of substituting between different vehicle types using the same stacked DiD model as in Equation (2). In this analysis, the outcome variable is changed to an indicator for four-wheeler purchases at the transaction level, where the indicator equals to 1 if the transaction involves a four-wheeler. The model continues to incorporate postal code and month fixed effects for each stack. Here, our coefficient of interest β, represents the probability of purchasing a four wheeler. By examining nearly 3 million vehicle registration records from April 2015 to February 2020, we find that there is indeed a shift from four-wheelers to two-wheelers. As shown in Table 5 Column (1), the probability that a registered vehicle is a four-wheeler decreases by 0.4% (significant at the 10% level) after the opening of a subway station. Thus, subway expansions seem to play in role in shifting automobile preferences.

$<$ Insert Table 5 here $>$

Next, we focus on the market share of automobiles. Using the absolute number of vehicles sold at the postal code level, we calculate the monthly market share of four-wheelers and assess the impact of subway expansions. By applying the same stacked DiD regression model as in our baseline specification, we observe a fall in the market share of four-wheelers, as shown in Table 5 Column (2). Specifically, the market share of four-wheelers fell by 1.2% (significant at the 1% level). This shift likely reflects households' growing preference for alternative modes of transport, particularly two- and three-wheelers, which are more practical for short trips between their residences and subway stations. With the introduction of the subway, households now have a cost-effective and convenient alternative to private car ownership, leading to a redistribution of transportation preferences and a corresponding drop in demand for four-wheelers.

We then turn our attention to the impact of subway expansions on vehicle sales and spending patterns, with a focus on the number of vehicles sold, average spending per vehicle, and total vehicle expenditures. The results, presented in Table 6 Panel A, show that subway expansions reduce demand for four-wheelers, while the effects on two- and three-wheelers are smaller and statistically insignificant. We find that the number of four-wheelers sold decreases by approximately 7 vehicles per month (significant at the 10% level), highlighting the direct impact of improved public transit access on the purchase of automobiles. In contrast, sales of two- and three-wheelers decline by about 2 units, though this reduction is not statistically significant at the 10 percent level. More importantly, the reduction in vehicle registrations translates into a significant drop in total spending on automobiles. We observe a 6.5% decrease in total vehicle expenditures in areas with new subway stations, which is statistically significant at the 5% level. This result underscores how subway expansions not only shift household preferences away from four-wheelers but also reduce overall vehicle spending in these regions. Moreover, the average spending per vehicle declines by 4.7% (significant at the 5% level), suggesting that households are increasingly opting for less expensive transportation options as they move away from private car ownership.

< Insert Table 6 here >

The impact of subway expansions on automobile purchases is expected to exhibit heterogeneity across households. Lower-income or financially constrained households are more sensitive to changes in transportation costs, as public transit offers a viable alternative to private vehicle ownership. In contrast, wealthier households are less likely to substitute automobiles for subways, as the marginal savings from reduced vehicle use may have a minimal impact on their overall financial situation. For them, convenience and status associated with car ownership may outweigh any potential financial benefits of using public transportation. While we lack direct income data for vehicle purchasers, we proxy household wealth by distinguishing between high-quality and low-quality vehicle purchases. It is plausible that wealthier households, with greater disposable income will purchase higher-quality vehicles. The underlying assumption here is that consumers are willing to pay more for vehicles perceived to be of higher quality, reflecting their greater financial capacity. High-quality vehicles are defined as those priced above the average within each vehicle category, while low-quality vehicles fall below the average price. As highlighted earlier, for two- and three-wheelers, high-quality vehicles are those priced above ₹68,376, while for four-wheelers, high-quality vehicles are those priced above ₹840,663. In doing so, we can indirectly assess the differential impact of subway expansions across income groups.

We divide our analysis into high- and low-quality vehicle registrations to explore whether the effects of subway expansions are primarily driven by financially constrained households. The results are presented in Table 6 Panel B. Here, we find that the majority of changes in four-wheeler registrations involve low-quality automobiles. After the opening of a subway station, the number of low-quality four-wheeler registrations decreases by 9 vehicles (statistically significant at the 5% level). In contrast, there is a modest increase of approximately 2 vehicles in high-quality four-wheeler registrations (statistically significant at the 10% level). Therefore, our findings suggest that higher-income households, who tend to purchase high-quality vehicles, do not substitute their four-wheelers for subway use. On the other hand, lower-income households, who tend to purchase lower-quality vehicles, appear to benefit financially from improved public transportation access. It is plausible that they are substituting private vehicle usage with the subway, freeing up financial resources for other expenses, such as mortgage payments.

4.2 Additional Evidence of Income

We now return to the mortgage dataset. Although the vehicle dataset lacks direct income information for buyers, the mortgage dataset offers detailed income data for borrowers. To strengthen the connection between the two datasets, we examine the heterogeneous effects of subway expansions by analyzing household responses across different income levels. This approach allows us to more precisely assess how subway expansions affect mortgage delinquency and prepayment decisions across income groups. By connecting vehicle types, as a proxy for wealth, with the income data from the mortgage dataset, we gain deeper insights into how lower-income households benefit from reduced vehicle expenses, while wealthier households may experience minimal financial impact from improved public transportation. As such, we can test whether income constraints are the key driver behind our results.

Formally, we examine the effect by estimating the following regression model:

$$Y_{ijm} = \beta \cdot Treated_{im} \cdot Post_{jm} + \sum_{k \in K} \beta_k \cdot Treated_{im} \cdot Post_{jm} \cdot I_{jk} + \mu_{ij} + \lambda_{jm} + \varepsilon_{ijm} \quad (3)$$

where K is a leave-one-out set of mortgage applicant characteristics. Categorical variable I_{jk} equals to 1 if a applicant is in a group with characteristic k. The base category is the characteristic being dropped. Then each β_k can be interpreted as the differences in the effects of metro expansions on mortgage delinquency and prepayment, compared applicants with characteristic k to those with corresponding base category.

Our hypothesis is that lower-income households are more likely to switch from private vehicles to subway transportation, which may improve their financial flexibility. However, some low-income households may not be able to afford a vehicle at all, limiting the benefits they gain from subway expansions. To account for this variation, we divide households into three groups: lowest-income (below the 25th percentile), lower-middle-income (between the 25th and 50th percentiles), and above-median (above the 50th percentile). This approach helps us better identify differences in financial behavior across income levels. With reference to Equation (3), the above-median group serves as the omitted category for comparison. We present the results in Table 7.

< Insert Table 7 here >

Consistent with our findings in the vehicles market, we observe that lower-middle-income households experience a 5.86% larger decrease in delinquency rates (significant at the 1% level) and a 52.5% greater reduction in delinquency amounts (significant at the 1% level) compared to households with income above the median. Additionally, the prepayment rate and amount for lower-middle-income households increase by 3.7% (significant at the 10% level) and 37.8% (significant at the 5% level), respectively, more than their above-median counterparts following subway expansions. In contrast, the effects of subway expansions on delinquency and prepayment for lowest-income households are not significantly different from those observed in households with income above the median. Our findings highlight the key role of automobile expenditures in mortgage repayments. Lower-middle-income households are more likely to replace private vehicle use with subway transportation, enhancing their financial flexibility. However, lowest-income households, who likely could not afford private vehicles prior to the subway expansions, do not benefit from reduced vehicle expenditures.

Previous studies have often grouped households into broad high- and low-income categories, implying similar welfare effects from commuting improvements across these groups (Balboni et al. (2020); Lee and Tan (2024)). By focusing on automobile purchases, we extend their work by distinguishing between lowest-income and lower-middle-income households, offering a more detailed view of how subway expansions affect different socioeconomic groups. Through these differences, we provide clearer insights into how public transportation infrastructure can ease financial pressures, particularly for households with limited resources, but not at the very bottom of the income scale. This distinction helps guide more targeted policy interventions to maximize the social and financial benefits of transportation improvements.

5 Discussion

In this section, we explore alternative explanations for how subway expansions might affect household mortgage behaviors. Beyond reduced automobile expenditures, subway expansions could enhance household finances by increasing individual income and driving economic growth in nearby areas. To test these, we examine two key hypotheses: first, that subway expansions boost labor productivity and income; and second, that these expansions fuel local economic growth, leading to better mortgage performance. We then evaluate the robustness of our findings through additional tests. Finally, we discuss the policy implications, emphasizing the broader benefits of subway expansions for mortgage markets and household financial stability.

5.1 Other Channels

There are several alternative channels through which subway expansions may affect households' decisions to fall behind on mortgage payments or prepay their mortgages. One potential channel is through improved access to higher-paying jobs and increased productivity, which could boost individual incomes. With reduced commuting times and better connectivity, individuals may find it easier to pursue new employment opportunities or work more efficiently, leading to enhanced financial stability. Another channel is through accelerated economic growth in areas surrounding new subway stations. As these regions develop more rapidly than others, rising property values and improved local economic conditions could enhance household finances and reduce mortgage delinquency. In what follows, we test these alternative explanations.

5.1.1 Individual Income

We begin by examining the individual income effect, where subway expansions might increase labor productivity and workforce participation, resulting in higher incomes. It is possible that the reduction in commuting time due to subway expansions could boost worker productivity (Xiao et al. (2021)), leading to higher wages and bonuses from improved job performance (Mulalic et al. (2014)). As a result, individuals living closer to subway stations could earn higher salaries, making them less likely to be delinquent and more likely to prepay their mortgages. While we lack labor market data at the postal code level in Delhi to directly test this channel, the rich demographics in our dataset allow us to explore it indirectly.

Here, we test the hypothesis of increased labor productivity by comparing the effects of subway expansions on residents working in the public sector versus those in the private sector. The rationale is that salaries in private sector jobs are more performance-based than those in the public sector. If this channel holds, we would expect private sector workers to be financially better off and therefore less delinquent or more likely to prepay after subway expansions. Formally, we classify applicants into public and private sector occupations. In our sample, public sector occupations include central government services, defense establishments, public sector undertakings, and state government services.

Thereafter, we run our benchmark regression again. However, Table A.1 Panel A shows no evidence of heterogeneity between public and private sector occupations. This evidence suggests that the productivity or bonus channel is not driving the observed improvements in mortgage performance after subway expansions. Instead, the improvements are likely attributable to other factors, such as transportation cost savings.

Another potential channel is that subway expansions may increase labor supply or participation rates by reducing commuting time and costs (Gutiérrez-i Puigarnau and van Ommeren (2010)). A higher labor participation rate would likely lead to increased household income, potentially improving mortgage performance. To test this mechanism, we examine the heterogeneous effects by gender. The rationale behind this approach is that, if the labor supply channel holds, women—who often face greater time constraints related to commuting and household responsibilities—might be more likely to enter the workforce or increase their working hours when commuting becomes easier. This, in turn, would reduce their likelihood of mortgage delinquency or increase their propensity to prepay. However, as shown in Panel B of Table A.1, our findings suggest that the effects of subway expansions on delinquency and prepayment do not differ significantly between men and women. Thus, we do not find evidence that increased labor supply, particularly among women, is the driving mechanism through which subway expansions influence mortgage outcomes.

We can also use household income data from our dataset to further rule out the income effect of subway expansions. When households apply for their mortgages, they disclose their annual income, giving us each borrower's income at the time of mortgage origination. However, since this income data is only reported once, it remains time-invariant. As a result, we cannot directly use a Difference-in-Differences approach to compare income levels before and after subway expansions. To address this limitation, we aggregate household income at the postal code and monthly levels. Specifically, for each postal code and month, we calculate the average annual income of households residing in the area and initiating mortgages during that time. This process yields a panel dataset of average income by postal code and month. Based on this data, we compare changes in income at the postal code level before and after subway expansions.[10] Columns (1) and (2) of Table A.2 report the changes in income following subway expansions. Interestingly, we observe a slight decrease in annual income after the expansions, further reinforcing that the income channel is unlikely to explain our results. This finding suggests that other factors, rather than increased income, are driving the observed improvements in mortgage performance.

[10]Note that we include households who purchased properties after the subway expansions, meaning their income is documented after the expansions, providing us post-treatment data on income.

5.1.2 Macroeconomic Conditions

Another potential channel through which subway expansions affect mortgage delinquency and prepayment is improved macroeconomic conditions. Areas benefiting from new subway infrastructure may experience faster economic growth compared to other regions, leading to stronger mortgage performance. This growth could be driven by increased accessibility, rising property demand, and overall urban development. For example, it is plausible that subways contribute to higher housing prices, which in turn can impact loan dynamics by increasing household equity or incentivizing more stable mortgage payments.

We test the economic growth channel by comparing the value of property and the amount of loans before and after subway expansions. Similar to constructing the panel data on average income, we aggregate property value and loan amount on mortgage origination at the postal code level. Our panel data then contains the average monthly present value of property and loan amount by postal code level and month. We apply the same stacked DiD regression as our baseline specification. Columns (3) to (6) of Table A.2 report the estimates of the changes in property value and loan amount after station opening.[11] Evidently, there is no economically and statistically significant evidence that the value of property and loan amount changed as a result of the expansions.

In addition, we rule out the housing price channel by examining the heterogeneous effects based on loan-to-value (LTV) ratios. Higher housing prices typically reduce the probability of negative equity, which occurs when the value of a property falls below the outstanding mortgage balance, often leading to fewer strategic defaults. Borrowers with higher LTV ratios are at greater risk of negative equity, so if our results were primarily driven by rising property values, we would expect them to be less delinquent following subway expansions. However, as shown in Table A.3, the evidence suggests otherwise. Households with higher LTV ratios did not benefit more from subway expansions; in fact, their delinquency rates increased by 4.33% (significant at the 10% level) relative to households with lower LTV ratios. This suggests that subway expansions are unlikely to reduce delinquency and increase prepayment through the housing price channel. Our findings align with Severen (2023), who find minimal effects of subways on local productivity or housing markets based on evidence from the Los Angeles Metro Rail.

5.2 Robustness

We now address potential concerns about our study by conducting several robustness tests. First, we analyze the full sample, which includes households that purchased properties after the subway expansions. We restrict the sample in our main results to reduce

[11] The numbers of observation for income and loan amount are much less than that for housing value as there are many missing values on annual income and loan amount.

the potential selection bias that could arise if individuals bought properties specifically due to their preference for proximity to public transit. The regression results in Table A.3 and event study graphs in Figure A.3 demonstrate that the full sample results are closely aligned with those from the restricted sample, suggesting that selection bias is not a significant concern. However, the dynamic effects on prepayment rates and amounts become insignificant when including households who bought properties post-expansion. This is likely because these households are in the early stages of their mortgages, where they tend to be less financially stable and have lower disposable income. Additionally, during the initial years of a mortgage, a larger portion of payments goes toward interest rather than principal, reducing the incentive for early prepayment.

Another concern involves the potential endogeneity at the postal code level, as subway stations in Delhi may be more likely to be constructed in areas with stronger economic conditions. This could lead to better mortgage performance in those areas, independent of the subway expansion itself. If this were the case, it might bias our results, as households in economically advantaged areas could naturally exhibit lower delinquency and higher prepayment rates. However, this should not pose a significant problem for the validity of our specification as long as these areas do not show divergent trends in mortgage delinquency and prepayment prior to the subway expansion. Importantly, if subway stations are more likely to be built in areas with initially better mortgage performance, our estimates of the effect of subway expansions on mortgage outcomes might actually be conservative. In other words, the true reductions in delinquency and increases in prepayment rates could be larger in a scenario where subway stations are randomly distributed across different postal code areas.

To mitigate the concern about endogeneity, we also include postal code level fixed effects to our baseline specification. This approach helps control for unobservable factors at the postal code level—such as neighborhood characteristics or economic conditions—that could influence mortgage performance. If the initial levels of mortgage performance are driven by factors fixed within postal codes, these fixed effects should capture that variation. As shown in Table A.5, our results on delinquency and prepayment remain robust,[12] suggesting that endogeneity at the postal code level is unlikely to be a major issue. This robustness is further reinforced by our use of individual-level data, which inherently helps address some of the concerns tied to postal code-level variations.

Moreover, there may be concerns that our findings are influenced by confounding time trends coinciding with the subway expansions. To address this, we conduct a placebo test by examining data from three years prior to the actual expansions and running the same

[12]Figure A.4 reports the event study graphs of specification with postal code fixed effects. The graphs are similar with the graphs based on our baseline specification. There is no evidence of pre-treatment trends.

stacked regression using this placebo event. If our results are genuinely driven by subway expansions and not by unrelated time trends, the placebo event should show no significant effects. As shown in Table A.6, the placebo test reveals no significant effects on any of the dependent variables, confirming that our findings on delinquency and prepayment are not influenced by external trends. Additionally, we address potential concerns about the use of logarithmic transformations for count-like variables by applying an alternative transformation, the inverse hyperbolic sine (IHS). This approach is particularly useful when handling zero or small values in the data. As presented in Table A.7, the results using the IHS transformation are consistent with our baseline findings, reinforcing the robustness of our conclusions across different modeling techniques.

An additional factor to consider is the influence of financing conditions such as fluctuations in Indian interest rate between 2015 and 2019. During this period, interest rates declined from 8.5% in April 2015 to 5.4% by February 2020. Lower interest rates can stimulate economic activity, leading to lower mortgage delinquency and increased prepayment rates. While we control for time-fixed effects to account for broad interest rate changes that affect all households, there remains a concern that households in postal codes with subway stations might respond more strongly to these rate reductions, potentially skewing our results. To alleviate this concern, we focus on a sub-sample of households with floating mortgage interest rates. Floating rates are directly tied to market fluctuations, meaning these borrowers should be more responsive to changes in interest rates compared to those with fixed-rate mortgages. If our results are driven primarily by interest rate changes, we would expect to see significant differences in the impact of subway expansions on households with floating rates. However, Table A.8 shows that the results for this sub-sample do not differ significantly from our baseline estimates, indicating that our findings are robust to interest rate fluctuations. Moreover, if interest rates were the primary driver of our results, we would expect the effects to be uniform across postal code areas. Yet, as shown in Table 4, the effects are more pronounced in areas farther from subway stations, suggesting that the primary factor influencing our results is indeed the subway expansions and not interest rate changes.

Lastly, we address the potential for households to anticipate subway expansions when purchasing properties, which could introduce selection bias. Although we restrict our sample to households that purchased properties before the actual expansion dates, it is possible that some buyers anticipated the future availability of subway stations and acted accordingly. However, the average time gap between property purchases and subway expansions in our sample is around five years, which reduces the likelihood of this anticipation influencing our results. Furthermore, the consistency of our results between the full and restricted samples suggests that any selection bias is minimal, and our findings remain robust.

5.3 Policy Implications

Our study carries far-reaching policy implications, particularly in the context of enhancing financial stability through urban infrastructure investments. While subways are commonly recognized for their role in improving urban mobility and connectivity across cities worldwide (Cheng and Chen (2015)), our findings suggest that their benefits extend beyond transportation. By reducing commuting costs and automobile expenditures, subway expansions can directly influence household financial well-being, particularly in the mortgage market. The ability to reallocate savings from reduced transportation expenses toward mortgage payments not only improves households' financial health but also contributes to greater overall economic stability. Additionally, these findings emphasize the potential of sustainable public transportation investments to deliver financial benefits to households. Through reduced transportation expenditures and improved cash flow, subway expansions contribute to better mortgage repayment outcomes, showcasing an often-overlooked financial advantage of sustainable infrastructure projects.

Mortgages are a critical component of household finances, and the inability to make timely mortgage payments has profound implications. For households, delinquency can lead to ineligibility for public housing assistance and restricted access to credit markets (Collinson et al. (2024)), while also negatively affecting overall household welfare (Diamond et al. (2020)). For the broader economy, mortgage delinquencies and foreclosures impose significant costs, potentially exacerbating housing downturns (Campbell et al. (2011); Guren and McQuade (2020)). On the flip side, mortgage prepayment benefits both households and the macroeconomy by reducing interest costs and facilitating savings. Prepayments also play a crucial role in the transmission of monetary policy to real economic activity (Beraja et al. (2019)). In this context, our findings are particularly relevant for hand-to-mouth households, which form a large segment of the economy. These households typically have limited access to liquid assets and are highly vulnerable to financial shocks (Gelman (2022); Aguiar et al. (2024)). For such households, automobile expenditures can severely restrict their ability to manage mortgage payments. Subway expansions that reduce transportation costs offer a crucial financial flexibility boost, easing financial pressures and allowing these households to meet their mortgage obligations.

To further quantify the broader impact of subway expansions on mortgage default rates, we conduct a back-of-the-envelope calculation using prior estimates of foreclosure probabilities. In particular, we estimate the potential reduction in mortgage default rates driven by the observed decrease in delinquency rates following subway expansions. Due to the limitations in our dataset, which does not capture exact default dates for many households beyond our sample period, we rely on this back-of-the-envelope estimation instead of applying the stacked difference-in-differences methodology used elsewhere in the paper. Formally, we define $P(Delinquency|M)$ and $P(Delinquency|-M)$ as the probabilities of delinquency for properties with and without nearby subway stations, respectively. Let $P(Default|Delinquency)$ represent the probability of default given delinquency. The reduction in the probability of default due to subway expansions, denoted by $P(Default|-M) - P(Default|M)$, can then be written as: $[P(Delinquency|-M) - P(Delinquency|M)] \times P(Default|Delinquency)$.

Our baseline specification estimates the change in the delinquency rate following subway expansions to be $[P(Delinquency|-M) - P(Delinquency|M)] = 0.0442$. To estimate the probability of default given delinquency, we use our loan-level data for February 2020, where $P(Default|Delinquency) \approx 0.019$.[13] Based on these values, our calculation suggests that the probability of default decreases by: $0.0442 \times 0.019 \approx 0.08\%$ for households in postal code areas with subway expansions. Out of the 9,681 mortgages in Delhi during our sample period, 72 (0.74%) ended in default. Thus, subway expansions result in an approximate 11% relative decrease in the default rate. These findings demonstrate the potential for infrastructure investments to reduce financial distress. Policymakers should thus consider the far-reaching benefits of urban transport projects, not only in terms of environmental sustainability and mobility but also in supporting financial security for vulnerable households.

6 Conclusion

In this paper, we highlight a crucial yet often overlooked connection between urban infrastructure and household financial health. Subway expansions not only promote environmental sustainability by reducing carbon emissions but also strengthen household finances by lowering transportation costs, allowing households to make more timely mortgage payments. This dual impact makes a strong case for viewing public transit investments as both environmental solutions and economic tools that enhance financial stability and resilience.

Analyzing the phased expansions of the Delhi Metro between 2015 and 2019, we find that new subway stations led to a 4.42% reduction in mortgage delinquency rates and a 1.38% increase in prepayment rates for households in the same postal code. These effects weaken with increasing distance from the station, indicating spillover effects. The improvement in mortgage outcomes is primarily due to reduced automobile expenses,

[13] Based on our data, there were 2,847 delinquent households as of February 2020. Among these, 53 households ultimately went into default. This method follows Gallagher et al. (2019) who estimate a foreclosure completion probability of 0.18 for delinquent mortgages using Fannie Mae loan performance data.

as financially constrained households shift away from private vehicle ownership. Vehicle registration data confirms that households near new subway stations spend less on automobiles, particularly on lower-quality vehicles. In doing so, they can redirect funds toward mortgage payments.

Our estimates carry direct policy implications, particularly in the context of global efforts to expand public transportation as a means of reducing carbon emissions. There is a compelling case for increased investment in subway networks as they can alleviate financial pressures on households. Back-of-the-envelope calculations suggest that subway expansions could reduce mortgage default rates by 0.08%, generating significant social and economic benefits. These broader impacts highlight the importance of aligning transportation infrastructure with urban development and financial inclusion strategies.

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Tables and Figures

Table 1: Summary Statistics

	Full Sample			Control			Treated		
	Obs.	Mean	St.Dev.	Obs.	Mean	St.Dev.	Obs.	Mean	St.Dev.
Panel A: Mortgage Variables									
Delinquency	361,598	0.29	0.45	177,054	0.30	0.46	184,544	0.28	0.45
Delinquency Amount	361,598	7,212	76,414	177,054	5,581	31,680	184,544	8,777	102,340
Prepayment	361,598	0.60	0.49	177,054	0.58	0.49	184,544	0.62	0.48
Prepayment Amount	361,598	84,420	373,027	177,054	69,264	286,196	184,544	98,963	440,040
Monthly Installment	361,598	24,271	88,764	177,054	21,865	64,955	184,544	26,579	106,675
Fixed Interest Rate	9,681	0.14	0.34	5,385	0.11	0.32	4,296	0.17	0.37
Loan Tenure	9,681	7,632	2,069	5,385	7,636	2,168	4,296	7,629	1,938
Loan to Value Ratio	9,681	0.56	0.25	5,385	0.58	0.25	4,296	0.54	0.24
Panel B: Demographic Variables									
Male	9,681	0.69	0.46	5,385	0.68	0.47	4,296	0.70	0.46
Age	9,681	49	10	5,385	48	10	4,296	50	10
Private Company	9,681	0.65	0.48	5,385	0.64	0.48	4,296	0.67	0.47
Annual Income	6,761	413,053	1,563,601	3,782	395,791	1,030,151	2,979	434,967	2,049,765

Notes: This table reports the means and standard deviations of mortgage and demographic variables using the full sample, the sample in the postal codes without subway expansions (Control), and the sample in the postal codes with subway expansions from April 2015 to February 2020. Variable *Fixed Interest Rate* is an indicator for individuals whose mortgage interest rate is fixed and variable *Private Company* is an indicator for those who do not work for public sector or government.

Table 2: Summary Statistics - Vehicle

	Full Sample			Control			Treated		
	Obs.	Mean	St.Dev.	Obs.	Mean	St.Dev.	Obs.	Mean	St.Dev.
Panel A: Transaction Level									
Two- and Three-Wheeler	3,191,266	0.74	0.44	1,483,656	0.75	0.43	1,707,610	0.74	0.44
Four-Wheeler	3,191,266	0.26	0.44	1,483,656	0.25	0.43	1,707,610	0.26	0.44
Price of Two- and Three-Wheeler	2,374,082	68,376	1,457,884	1,112,770	66,246	200,628	1,261,312	70,255	1,991,237
Price of Four-Wheeler	817,184	840,663	1,039,530	370,886	813,157	1,019,981	446,298	863,521	1,054,956
Panel B: Postal Code Level									
Two- and Three-Wheeler	5,722	415	490	3,303	337	412	2,419	512	563
Two- and Three-Wheeler (High Quality)	5,722	85	102	3,303	70	87	2,419	106	117
Two- and Three-Wheeler (Low Quality)	5,722	330	396	3,303	267	333	2,419	415	454
Four-Wheeler	5,722	143	127	3,303	112	113	2,419	184	133
Four-Wheeler (High Quality)	5,722	41	41	3,303	31	36	2,419	55	43
Four-Wheeler (Low Quality)	5,722	102	93	3,303	81	82	2,419	129	101
Average Spending	5,722	13	0.66	3,303	12	0.73	2,419	13	0.53
Total Spending	5,722	18	1.59	3,303	18	1.86	2,419	19	0.76

Notes: This table reports the means and standard deviations of variables at transaction level (Panel A) and postal code level (Panel B) using the full sample, the sample in the postal codes without subway expansions (Control), and the sample in the postal codes with subway expansions from April 2015 to February 2020. Variables are the monthly registration indicator for two- and three-wheeler, indicator for four-wheeler, price of two- and three-wheeler, and price of four-wheeler at individual level.

Table 3: Stacked DiD Estimates for Subway Expansions - Mortgage

Dependent Variable:	Indicator for Delinquency (1)	Log(Delinquency Amount) (2)	Indicator for Prepayment (3)	Log(Prepayment Amount) (4)
$Treated \times Post$	-0.0442***	-0.392***	0.0138**	0.102
	(0.0101)	(0.0892)	(0.00701)	(0.0746)
Observations	2,484,192	2,484,192	2,484,192	2,484,192
R^2	0.597	0.603	0.684	0.737
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

Notes: Based on the mortgage repayment records in Delhi, this table reports the impact of the opening of a subway station between 2015 and 2019. The dependent variables encompass the indicator for delinquency, delinquency amount, the indicator for prepayment, and prepayment amount. The amounts are reported in their logarithm values. For the independent variable, $Treated \times Post$ an indicator variable that is equal to one after the opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively.

Table 4: Stacked DiD Estimates for Subway Expansions - Restricted Control Groups

Panel A: Close Postal Code Areas				
Dependent Variable:	Indicator for Delinquency	Log(Delinquency Amount)	Indicator for Prepayment	Log(Prepayment Amount)
	(1)	(2)	(3)	(4)
Treated × *Post*	-0.0249**	-0.257***	0.00611	0.0798
	(0.0103)	(0.0967)	(0.00697)	(0.0776)
Observations	1,062,759	1,062,759	1,062,759	1,062,759
R^2	0.606	0.605	0.684	0.738
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes
Panel B: Far Postal Code Areas				
Dependent Variable:	Indicator for Delinquency	Log(Delinquency Amount)	Indicator for Prepayment	Log(Prepayment Amount)
	(1)	(2)	(3)	(4)
Treated × *Post*	-0.0572***	-0.487***	0.0193**	0.120
	(0.0103)	(0.0925)	(0.00755)	(0.0778)
Observations	1,605,977	1,605,977	1,605,977	1,605,977
R^2	0.593	0.603	0.683	0.736
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the impact of the opening of a subway station between 2015 and 2019, based on two different control groups. Panel A (B) presents the results using the postal code areas close to (far from) the treatment areas as the control group. The dependent variables encompass the indicator for delinquency, delinquency amount, the indicator for prepayment, and prepayment amount. The amounts are reported in their logarithm values. For the independent variable, $Treated \times Post$ an indicator variable that is equal to one after the opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively.

Table 5: Stacked DiD Estimates for Subway Expansions - Four Wheeler Purchase

Dependent Variable:	Indicator for Four-Wheeler	Share of Four-Wheeler
	(1)	(2)
$Treated \times Post$	-0.00391*	-0.0120***
	(0.00237)	(0.00396)
Observations	20,995,138	45,358
R^2	0.073	0.554
Month Fixed Effects	Yes	Yes
Postal Code Fixed Effects	Yes	Yes

Notes: Based on the total number of registered vehicles in Delhi, this table reports the impact of the opening of a subway station between 2015 and 2019. The dependent variable in column (1) is an indicator for four wheelers, which is equal to one if the registered vehicle is a four-wheeler, and zero otherwise at the transaction level. In column (2), share of four-wheeler is the proportion of four-wheelers among all registered vehicle at the postal code level. For the independent variable, $Treated \times Post$ an indicator variable that is equal to one after the opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively

Table 6: Stacked DiD Estimates for Subway Expansions - Vehicle

Panel A: Vehicles Purchase				
Dependent Variable:	Two- and Three-Wheeler	Four-Wheeler	Average Spending	Total Spending
	(1)	(2)	(3)	(4)
Treated × *Post*	-2.236	-6.956*	-0.0469***	-0.0652**
	(9.560)	(3.673)	(0.0133)	(0.0256)
Observations	45,358	45,358	45,358	45,358
R^2	0.922	0.924	0.418	0.889
Month Fixed Effects	Yes	Yes	Yes	Yes
Postal Code Fixed Effects	Yes	Yes	Yes	Yes
Panel B: Vehicles Purchase (by type)				
Dependent Variable:	Two- and Three-Wheeler: High Quality	Two- and Three-Wheeler: Low Quality	Four-Wheeler: High Quality	Four-Wheeler: Low Quality
	(1)	(2)	(3)	(4)
Treated × *Post*	4.729	-6.965	2.079*	-9.034**
	(3.691)	(7.869)	(1.196)	(3.861)
Observations	45,358	45,358	45,358	45,358
R^2	0.860	0.914	0.910	0.903
Month Fixed Effects	Yes	Yes	Yes	Yes
Postal Code Fixed Effects	Yes	Yes	Yes	Yes

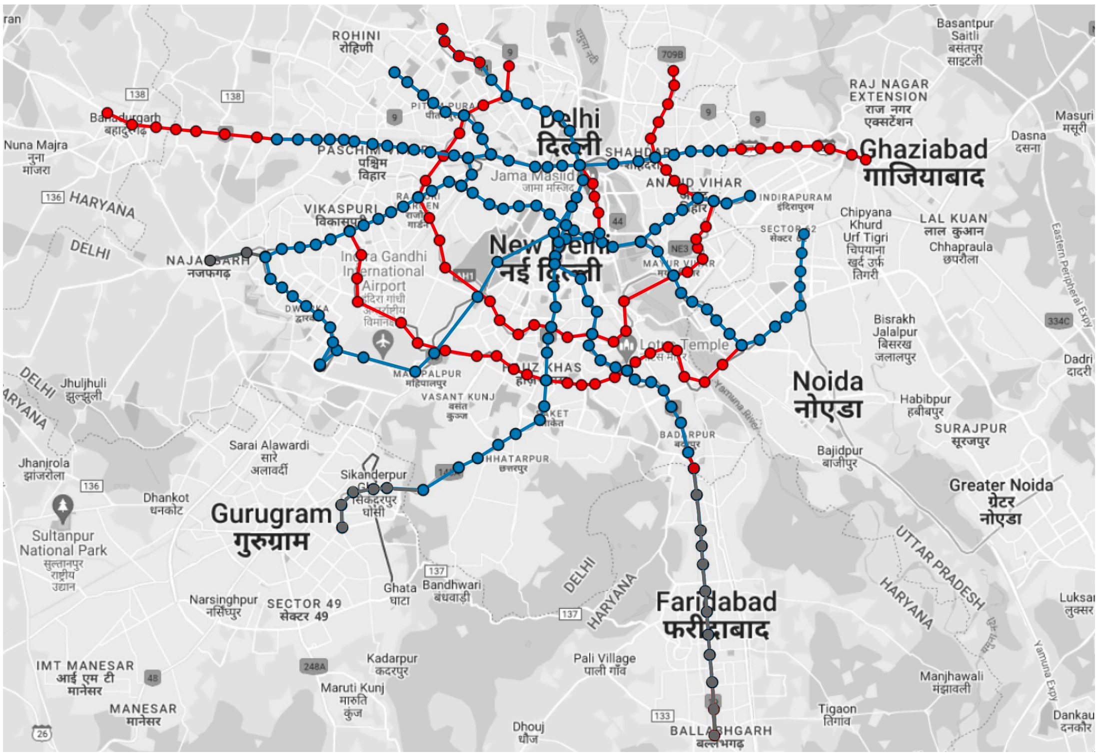
Notes: Based on data aggregated at the postal code level, this table reports the impact of the opening of a subway station on the purchase on vehicles within the same postal code area. The treatment indicator is equal to one after the opening of the subway station, and zero otherwise. In Panel A, the dependent variables include the absolute number of two- and three-wheelers, the absolute number of four-wheelers, the average costs of each vehicle, the total spending on vehicles at postal code level. In Panel B, the dependent variables relate to the quality of four-wheelers and two- and three-wheelers respectively. We consider a vehicle to be high (low) quality if its price is higher (lower) than the average price of the vehicle registered during the time period. Robust standard errors are in parentheses, clustered at postal code level. $*, **$ and $***$ denotes significance level at 10%, 5% and 1% respectively.

Table 7: Heterogeneous Effects based on Income

Dependent Variable:	Indicator for Delinquency	Log(Delinquency Amount)	Indicator for Prepayment	Log(Prepayment Amount)
	(1)	(2)	(3)	(4)
Treated × *Post*	-0.0404**	-0.325*	0.00986	0.0366
	(0.0180)	(0.168)	(0.0116)	(0.123)
Treated × *Post* × $\mathbb{1}$(Annual Income ≤ ₹100,000)	-0.0128	-0.110	-0.00154	0.118
	(0.0242)	(0.193)	(0.0231)	(0.267)
Treated × *Post* × $\mathbb{1}$(₹100,000 < Annual Income ≤ ₹400,000)	-0.0586***	-0.525***	0.0370*	0.378**
	(0.0200)	(0.180)	(0.0192)	(0.179)
Observations	1,101,831	1,101,831	1,101,831	1,101,831
R^2	0.584	0.593	0.681	0.733
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

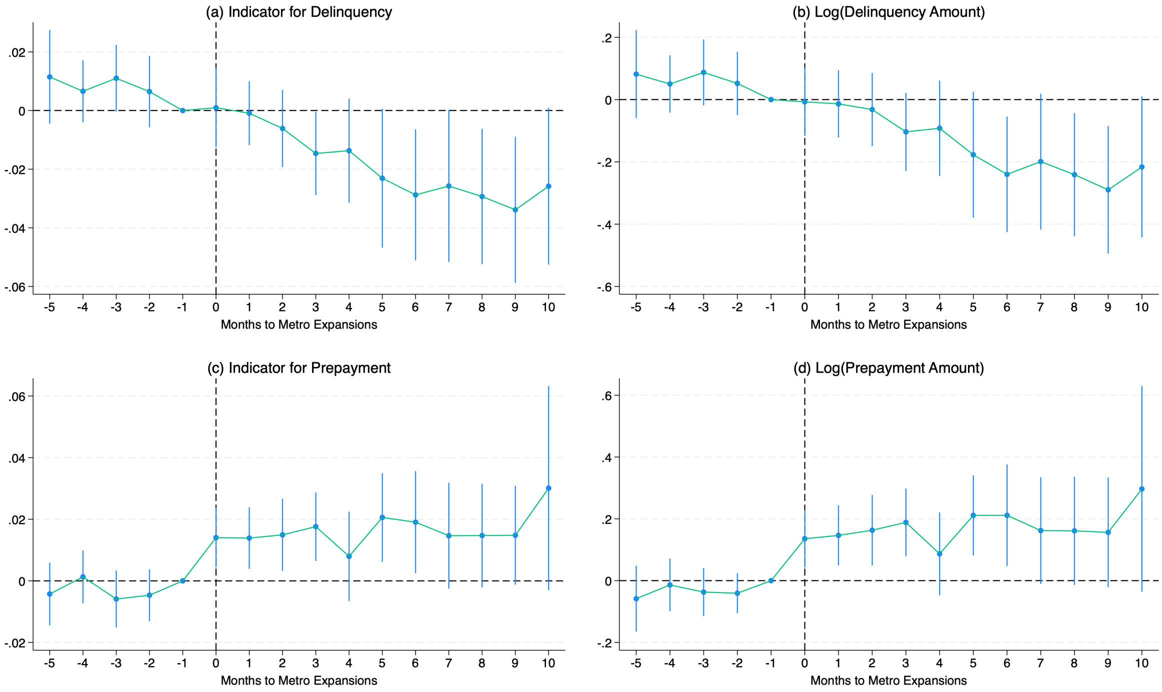
Notes: This table reports the heterogeneous effects of the opening of subway stations by household's annual income before subway expansions. The treatment indicator is equal to one after the opening of the subway station, and zero otherwise. ₹100,000 and ₹400,000 are the 25th and 50th percentile of annual income in our dataset. The base category is the households whose income is above the median. Robust standard errors are in parentheses, clustered at postal code level. $*, **$ and $***$ denotes significance level at 10%, 5% and 1% respectively.

Figure 1: Subway Expansions in Delhi



Notes: This figure presents the evolution of the subway stations in Delhi from 2015 to 2019. The blue circles represent existing subway stations till 2014, while the red circles refer to new subway lines that were built from 2015 to 2019. The grey circles are the stations built outside Delhi or after 2019.

Figure 2: Event Study of Subway Expansions



Notes: Panel (a), (b), (c), and (d) present the dynamic effects of subway expansions on indicator for delinquency, logarithmic delinquency amount, indicator for prepayment, and logarithmic prepayment amount respectively based on the baseline specification. Positive m refers to m_{th} months after expansions and negative m refers to m_{th} quarters before expansions. $m = 0$ refers to the month of subway expansions. We choose one month before expansions $m = -1$ as our base period. Vertical lines on dots denote 95 percent confidence interval.

Online Appendix

A Additional Graphs and Tables

Table A.1: Heterogeneous Effects of Subway Expansions by Demographic Characteristics

Panel A: Occupation				
Dependent Variable:	Indicator for Delinquency	Log(Delinquency Amount)	Indicator for Prepayment	Log(Prepayment Amount)
	(1)	(2)	(3)	(4)
$Treated \times Post$	-0.0559***	-0.547***	0.0156	0.0459
	(0.0151)	(0.135)	(0.00981)	(0.0934)
$Treated \times Post \times \mathbb{1}$(Private Company)	0.0172	0.226*	-0.00263	0.0814
	(0.0127)	(0.116)	(0.0115)	(0.100)
Observations	2,484,192	2,484,192	2,484,192	2,484,192
R^2	0.597	0.603	0.684	0.737
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes
Panel B: Gender				
Dependent Variable:	Indicator for Delinquency	Log(Delinquency Amount)	Indicator for Prepayment	Log(Prepayment Amount)
	(1)	(2)	(3)	(4)
$Treated \times Post$	-0.0455***	-0.409***	0.0241*	0.269*
	(0.0125)	(0.112)	(0.0125)	(0.152)
$Treated \times Post \times \mathbb{1}$(Male)	0.00192	0.0248	-0.0149	-0.240
	(0.0124)	(0.110)	(0.0126)	(0.163)
Observations	2,484,192	2,484,192	2,484,192	2,484,192
R^2	0.597	0.603	0.684	0.737
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the heterogeneous effects of the opening of subway stations by demographic characters. The treatment indicator is equal to one after the opening of the subway station, and zero otherwise. In Panel A, we divide our sample into the borrowers who work for private firms and those who work for public sector. Occupations in public sector include central government services, services in defence establishment, services in public sector undertaking, and state government services. In Panel B, we divide our sample into male and female borrowers. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denotes significance level at 10%, 5% and 1% respectively.

Table A.2: Stacked DiD Estimates for Subway Expansions - Income, Loan, and Value

Dependent Variable:	Annual Income	Log(Annual Income)	House Value	Log(House Value)	Loan Amount	Log(Loan Amount)
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated \times Post$	-58,229	-0.101	-574,132	-0.0183	-797,315	-0.154
	(50,084)	(0.130)	(878,874)	(0.0601)	(1.319e+06)	(0.373)
Observations	10,106	10,106	15,273	15,273	4,681	4,681
R^2	0.167	0.189	0.274	0.390	0.337	0.315
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Postal Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Based on data aggregated at the postal code level from April 2015 to February 2020, this table reports the impacts of the opening of a subway station on the annual income, housing value, and loan amount within the same postal code area. The treatment indicator is equal to one after the opening of the subway station, and zero otherwise. The dependent variables encompass the present value of properties and the amount of loan, including their logarithm values. Robust standard errors are in parentheses, clustered at postal code level. $*, **$ and $***$ denotes significance level at 10%, 5% and 1% respectively.

Table A.3: Heterogeneous Effects of Subway Expansions by Loan to Value (LTV) Ratio

Dependent Variable:	Indicator for Delinquency (1)	Log(Delinquency Amount) (2)	Indicator for Prepayment (3)	Log(Prepayment Amount) (4)
$Treated \times Post$	-0.0503***	-0.434***	0.0164**	0.119
	(0.0102)	(0.0913)	(0.00751)	(0.0827)
$Treated \times Post \times \mathbb{1}(\text{LTV} > 0.8)$	0.0433*	0.295	-0.0183	-0.121
	(0.0257)	(0.225)	(0.0255)	(0.257)
Observations	2,484,192	2,484,192	2,484,192	2,484,192
R^2	0.597	0.603	0.684	0.737
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the heterogeneous effects of the opening of subway stations by loan to value (LTV) ratio. The treatment indicator is equal to one after the opening of the subway station, and zero otherwise. We split all borrowers into two groups with cutoff LTV at 0.8. Borrowers with higher LTV are more likely to be strategic defaulters. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denotes significance level at 10%, 5% and 1% respectively.

Table A.4: Robustness Check - Full Sample

Dependent Variable:	Indicator for Delinquency (1)	Log(Delinquency Amount) (2)	Indicator for Prepayment (3)	Log(Prepayment Amount) (4)
$Treated \times Post$	-0.0442***	-0.392***	0.0143**	0.107
	(0.0102)	(0.0898)	(0.00703)	(0.0751)
Observations	2,517,460	2,517,460	2,517,460	2,517,460
R^2	0.597	0.603	0.684	0.737
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the impact of the opening of a subway station between 2015 and 2019, based on full sample. The dependent variables encompass the indicator for delinquency, delinquency amount, the indicator for prepayment, and prepayment amount. The amounts are reported in their logarithm values. For the independent variable, $Treated \times Post$ an indicator variable that is equal to one after the opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively.

Table A.5: Robustness Check - Fix Postal Code Effects

Dependent Variable:	Indicator for Delinquency (1)	Log(Delinquency Amount) (2)	Indicator for Prepayment (3)	Log(Prepayment Amount) (4)
$Treated \times Post$	-0.0442***	-0.392***	0.0138**	0.102
	(0.0101)	(0.0892)	(0.00701)	(0.0746)
Observations	2,484,192	2,484,192	2,484,192	2,484,192
R^2	0.597	0.603	0.684	0.737
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes
Postal Code Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the impact of the opening of a subway station between 2015 and 2019, based on the specification with postal code fixed effects. The dependent variables encompass the indicator for delinquency, delinquency amount, the indicator for prepayment, and prepayment amount. The amounts are reported in their logarithm values. For the independent variable, $Treated \times Post$ an indicator variable that is equal to one after the opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively.

Table A.6: Robustness Check - Placebo Test

Dependent Variable:	Indicator for Delinquency (1)	Log(Delinquency Amount) (2)	Indicator for Prepayment (3)	Log(Prepayment Amount) (4)
$Treated \times Post(Placebo)$	-0.0281	-0.225	0.0168	0.0607
	(0.0187)	(0.166)	(0.0137)	(0.147)
Observations	2,484,192	2,484,192	2,484,192	2,484,192
R^2	0.597	0.603	0.684	0.737
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the placebo impact of subway expansions, based on a set of fake subway station opening dates (3 years before the actual ones). The dependent variables encompass the indicator for delinquency, delinquency amount, the indicator for prepayment, and prepayment amount. The amounts are reported in their logarithm values. For the independent variable, $Treated \times Post(Placebo)$ an indicator variable that is equal to one after the fake opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively.

Table A.7: Robustness Check - Inverse Hyperbolic Sine Function

Dependent Variable:	Asinh(Delinquency Amount)	Asinh(Prepayment Amount)
	(1)	(2)
$Treated \times Post$	-0.423***	0.111
	(0.0961)	(0.0790)
Observations	2,484,192	2,484,192
R^2	0.603	0.735
Month Fixed Effects	Yes	Yes
Account Fixed Effects	Yes	Yes

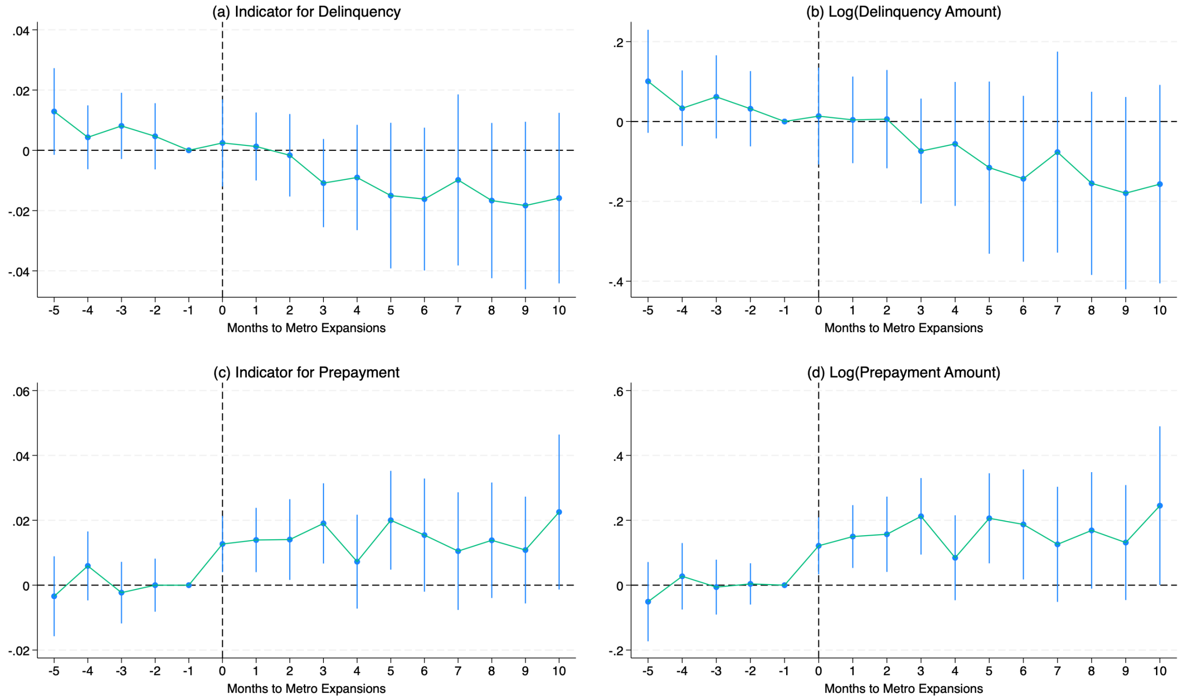
Notes: This table reports the impact of the opening of a subway station between 2015 and 2019. The dependent variables encompass delinquency amount and prepayment amount. The amounts are reported by inverse hyperbolic sine transformation. For the independent variable, $Treated \times Post$ an indicator variable that is equal to one after the opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively.

Table A.8: Robustness Check - Households with Floating Mortgage Rate

Dependent Variable:	Indicator for Delinquency (1)	Log(Delinquency Amount) (2)	Indicator for Prepayment (3)	Log(Prepayment Amount) (4)
$Treated \times Post$	-0.0496***	-0.431***	0.0193**	0.147
	(0.0109)	(0.0940)	(0.00849)	(0.0923)
Observations	2,125,124	2,125,124	2,125,124	2,125,124
R^2	0.599	0.605	0.686	0.739
Month Fixed Effects	Yes	Yes	Yes	Yes
Account Fixed Effects	Yes	Yes	Yes	Yes

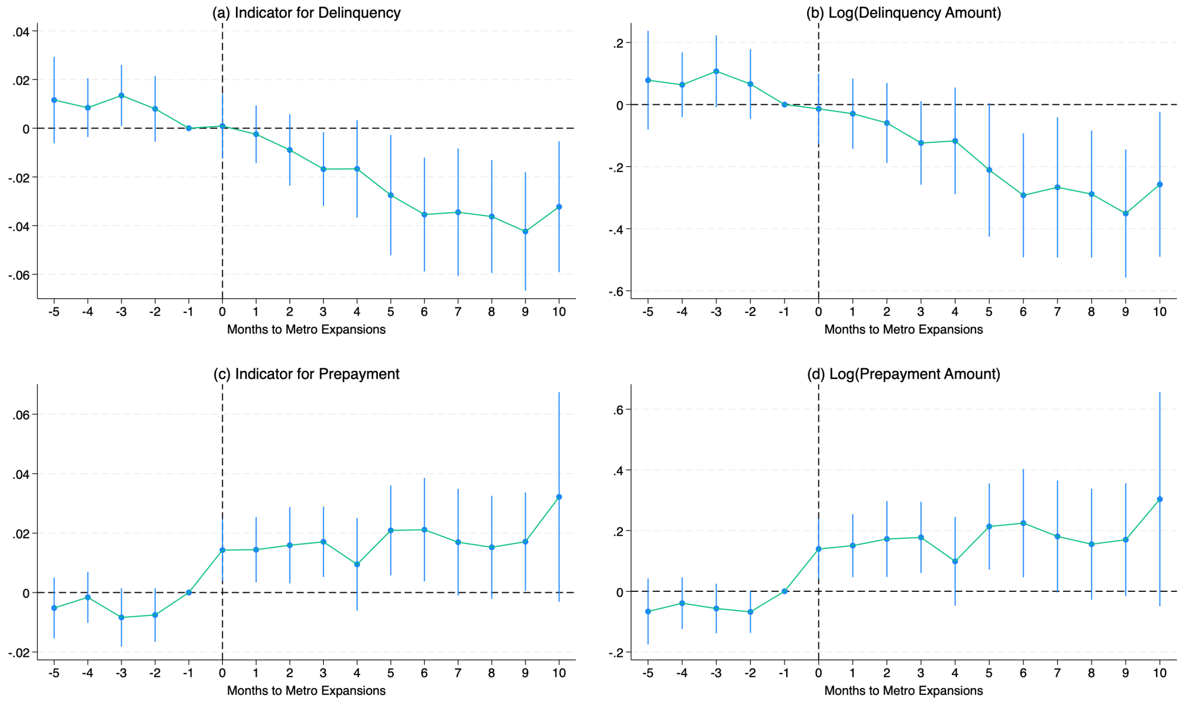
Notes: This table reports the impact of the opening of a subway station between 2015 and 2019, based on the sub-sample with households whose mortgage rate is floating. The dependent variables encompass the indicator for delinquency, delinquency amount, the indicator for prepayment, and prepayment amount. The amounts are reported in their logarithm values. For the independent variable, $Treated \times Post$ an indicator variable that is equal to one after the opening of the subway station in the same postal code, and zero otherwise. Clustering is done at the postal code level. The robust standard errors are reported in parenthesis. $*, **$ and $***$ denote statistically significant levels at 10%, 5% and 1% respectively.

Figure A.1: Event Study of Subway Expansions - Close Postal Code Areas



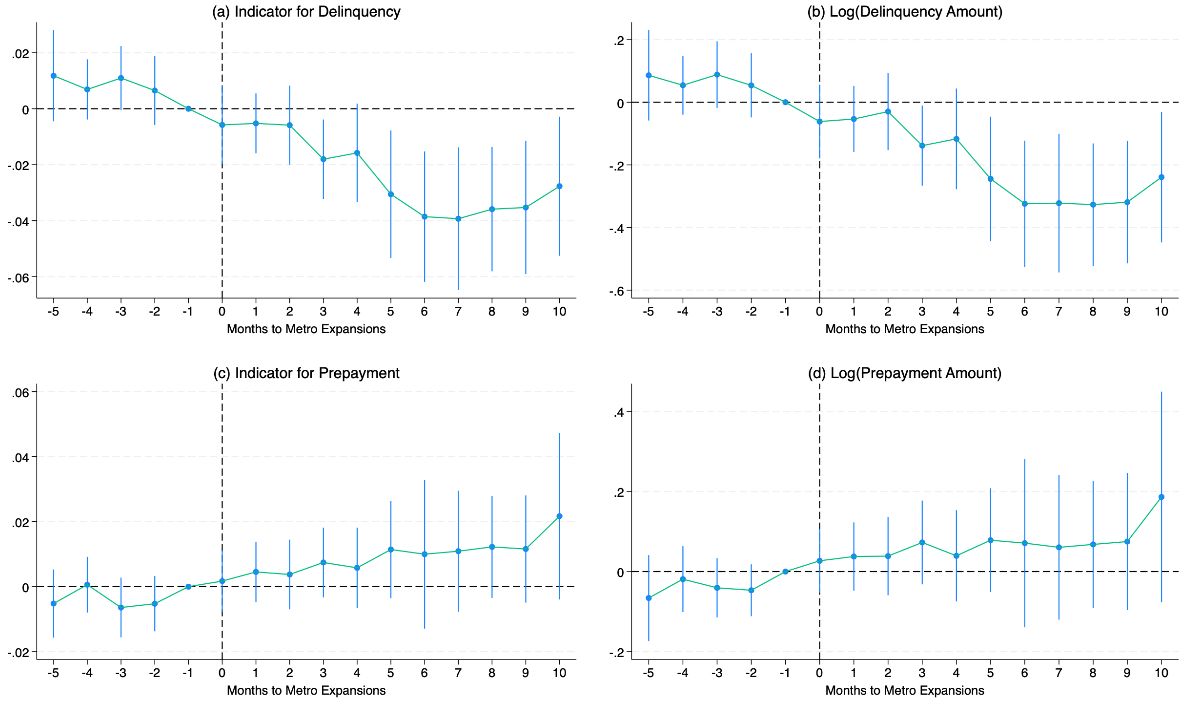
Notes: Panel (a), (b), (c), and (d) present the dynamic effects of subway expansions on indicator for delinquency, logarithmic delinquency amount, indicator for prepayment, and logarithmic prepayment amount respectively by using the postal code areas close to the treatment areas as the control group. Positive m refers to m_{th} months after expansions and negative m refers to m_{th} quarters before expansions. $m = 0$ refers to the month of subway expansions. We choose one month before expansions $m = -1$ as our base period. Vertical lines on dots denote 95 percent confidence interval.

Figure A.2: Event Study of Subway Expansions - Far Postal Code Areas



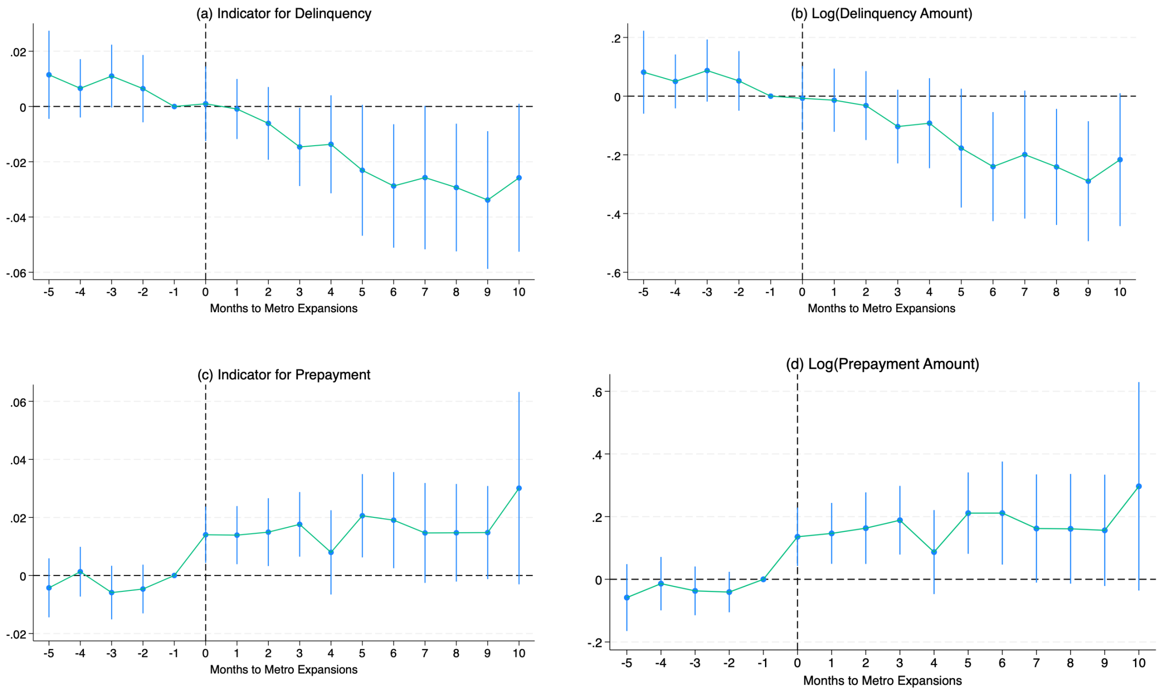
Notes: Panel (a), (b), (c), and (d) present the dynamic effects of subway expansions on indicator for delinquency, logarithmic delinquency amount, indicator for prepayment, and logarithmic prepayment amount respectively by using the postal code areas far from the treatment areas as the control group. Positive m refers to m_{th} months after expansions and negative m refers to m_{th} quarters before expansions. $m = 0$ refers to the month of subway expansions. We choose one month before expansions $m = -1$ as our base period. Vertical lines on dots denote 95 percent confidence interval.

Figure A.3: Robustness Check - Full Sample



Notes: Panel (a), (b), (c), and (d) present the dynamic effects of subway expansions on indicator for delinquency, logarithmic delinquency amount, indicator for prepayment, and logarithmic prepayment amount respectively, based on full sample. Positive m refers to m_{th} months after expansions and negative m refers to m_{th} quarters before expansions. $m = 0$ refers to the month of subway expansions. We choose one month before expansions $m = -1$ as our base period. Vertical lines on dots denote 95 percent confidence interval.

Figure A.4: Robustness Check - Fix Postal Code Effects



Notes: Panel (a), (b), (c), and (d) present the dynamic effects of subway expansions on indicator for delinquency, logarithmic delinquency amount, indicator for prepayment, and logarithmic prepayment amount respectively, based on the specification with postal code fixed effects. Positive m refers to m_{th} months after expansions and negative m refers to m_{th} quarters before expansions. $m = 0$ refers to the month of subway expansions. We choose one month before expansions $m = -1$ as our base period. Vertical lines on dots denote 95 percent confidence interval.