# Mortgages, Subways and Automobiles

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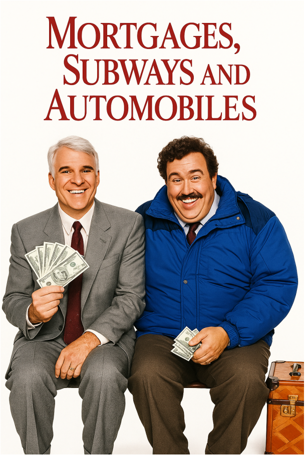
# Inspired by *Planes, Trains and Automobiles*


- In the movie, a journey full of missteps ends with a heartfelt reunion.

# Inspired by *Planes, Trains and Automobiles*




- In our case, a change in daily journeys leads to better financial outcomes.
- When subways expand, households rely less on cars.
- This shift frees up liquidity, helping them pay down mortgages.
- Not just fewer emissions, but fewer defaults.

# Background

- Many countries have developed their urban subway networks to reduce their emissions and improve urban mobility.

- Growing research on benefits of the subway:
  - **Direct benefits:** reductions in commuting costs (Gupta et al. (2022)), traffic congestion (e.g., Gu et al. (2021)), and air pollution (e.g., Li et al. (2019)).
  - **Spillover benefits:** increases in innovations (Koh et al. (2022)) and firm-level productivity (Chen and Wu (2024))

- However, direct evidence of subways on household finances remains relatively scarce.

# This Paper

- We investigate how subways could affect households' financial well-being through the mortgage market.

- Our setting combines:
  - A unique administrative dataset of mortgage loans in India.
  - The staggered rollout of subway stations across Delhi (2015–2019).

- **Main takeaway:** Subways ease financial pressure by reducing reliance on car ownership, allowing households to stay current on mortgages or prepay.

# Summary of Findings

- After new subway stations opened:
  - Delinquency rates fell by **4.42%**; total delinquent amounts dropped **39.2%**.
  - Prepayment rates rose by **1.38%**, with a sharp increase in prepayment amounts during the first 3 months.
  - Effects attenuate with distance from the nearest station.
- What explains these patterns?
  - Households spend less on automobiles
  - Monthly auto expenditures decline by **6.5%**.
  - This improves liquidity and frees up cash for mortgage repayment.

# Contribution to Literature

1. The Effects of Subways:
   - Gu et al. (2021), Lee and Tan (2024), Severen (2023), Zheng et al. (2016), Harris (2020), etc.

   Contribution: Focus on the effects on households' mortgage repayment decisions.
2. Mortgage Delinquency:
   - Kaufmann et al. (2011), Low (2023), Ganong and Noel (2023), etc.

   Contribution: Support the role of vehicle expenditures on mortgage delinquency.
3. Mortgage Prepayment:
   - Gerardi et al. (2023), Amromin et al. (2007), Scharlemann and Shore (2022), etc.

   Contribution: Connect mortgage delinquency and prepayment through contrasting impacts of subway expansions.

# Delhi Metro

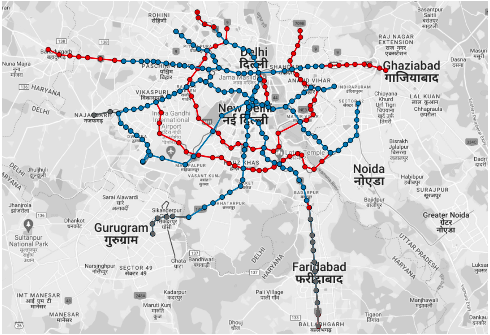
- Delhi's population exceeds 33 million, making reliable transit infrastructure critical.
- The Delhi Metro is one of the world's largest and busiest subway systems, operating over 3,000 trips daily and serving approximately 2.5 million passengers.
- It became the first metro globally to earn UN-certified carbon credits in 2011, reducing emissions by 630,000 tonnes annually.

# Phase 3 Expansion and Study Focus

- Phases 1, 2, and 3 were completed in 2006, 2011, and 2021, providing high-capacity, low-emission transportation across Delhi and the NCR.
- Our study focuses on **subway station openings between 2015 and 2019**, the bulk of Phase 3 expansion.
- Phase 3 added over 160 km of new lines, including the Magenta, Pink, and Grey Lines.
- The expansion aimed to enhance connectivity, reduce pollution, and improve quality of life.

# Subway Expansions in Delhi

- There are 100 postal codes in Delhi (110000 to 110099).
- On average, a postal code covers around a 2.18 km radius circle.
- Subway stations opened in 41 different postal code areas.
- Figure below maps pre-2014 (blue), 2015–2019 (red), and post-2019/outside Delhi (grey) subway stations.



# Mortgage Data

- The administrative data is from one of the largest mortgage lenders in India.
- The dataset is between April 2015 to February 2020.
- It contains detailed records of households' monthly mortgage payments and information of the mortgage applicants.
- We match the postal code of the mortgage applicants with the location of the subway station (Treatment Group).

# Key Outcome Variables

1. Indicator for Delinquency
2. Indicator for Prepayment
3. Delinquency Amount
4. Prepayment Amount

- Each month, a borrower is categorized as delinquent if the balance turns negative or as prepaid if it becomes positive.
- Delinquency or prepayment amount that is the difference between the cumulative installment and the repayment.

# Mortgage Data

Data restriction: only focus on the group of households who purchase their properties before subway expansions.

| | Full Sample | | | Control | | | Treatment | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | St.Dev. | Obs. | Mean | St.Dev. | Obs. | Mean | St.Dev. |
| **Mortgage Characteristics** | | | | | | | | | |
| Delinquency | 361,598 | 0.29 | 0.45 | 177,054 | 0.30 | 0.46 | 184,544 | 0.28 | 0.45 |
| Delinquency Amount | 361,598 | 7212 | 76414 | 177,054 | 5581 | 31680 | 184,544 | 8777 | 102340 |
| Prepayment | 361,598 | 0.60 | 0.49 | 177,054 | 0.58 | 0.49 | 184,544 | 0.62 | 0.48 |
| Prepayment Amount | 361,598 | 84420 | 373027 | 177,054 | 69264 | 286196 | 184,544 | 98963 | 440040 |
| Monthly Installment | 361,598 | 24271 | 88764 | 177,054 | 21865 | 64955 | 184,544 | 26579 | 106675 |
| 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 | 7632 | 2069 | 5,385 | 7636 | 2168 | 4,296 | 7629 | 1938 |
| Loan to Value Ratio | 9,681 | 0.56 | 0.25 | 5,385 | 0.58 | 0.25 | 4,296 | 0.54 | 0.24 |
| **Demographic Characteristics** | | | | | | | | | |
| 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 | 413053 | 1563601 | 3,782 | 395791 | 1030151 | 2,979 | 434967 | 2049765 |

# Baseline Specification

- The subway stations are opened at different timing
  $\implies$ staggered treatment timings.

- There are differences in subway stations in terms of size or commuting flow
  $\implies$ biased TWFE estimates.

- We estimate our results based on a stacked difference-in-differences model (following Deshpande and Li (2019), Cengiz et al. (2019)).

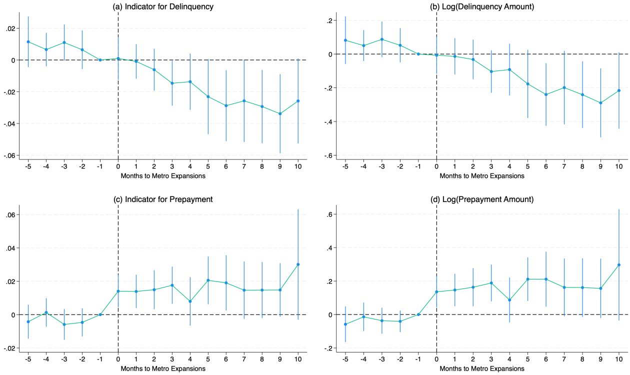
# Baseline Specification

The regression specification can be written as:

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

- $Treated_{im}$ 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.
- $\mu_{ij}$ is individual-by-stack fixed effect.
- $\lambda_{jm}$ refers to month-by-stack fixed effect.
- $\varepsilon_{ijm}$ is the error term.
- Standard errors are clustered by postal code, the level at which treatment is assigned.

# Baseline Specification




- Top Panel: There is a delayed effect, with delinquency beginning to decrease only from the third month after the expansions.
- Bottom Panel: There is an immediate increase in prepayment in the month of subway expansion.

# Baseline Specification

| Dependent Variable: | Indicator for Delinquency | Log(Delinquency Amount) | Indicator for Prepayment | Log(Prepayment Amount) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (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 |

# Different Control Groups by Distance

| **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 |

- In Panel A, we focus on the 29 neighboring areas whose postal code numbers are adjacent to the postal code numbers of the treatment areas.
- In Panel B, we consider the remaining 30 distant postal areas as the control.

# Automobile Purchases

- To test the channel of automobile expenditures, we use monthly automobile transaction data in Delhi.
- The dataset contains more than 3 million vehicle registration records of all the vehicle registrations in Delhi from April 2015 to February 2020.

| | Full Sample | | | Control | | | Treatment | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | St.Dev. | Obs. | Mean | St.Dev. | Obs. | Mean | St.Dev. |
| **Variable** | | | | | | | | | |
| Non-Four-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 Non-Four-Wheeler | 2,374,082 | 68376 | 1457884 | 1,112,770 | 66246 | 200628 | 1,261,312 | 70255 | 1991237 |
| Price of Four-Wheeler | 817,184 | 840663 | 1039530 | 370,886 | 813157 | 1019981 | 446,298 | 863521 | 1054956 |

- We test for the likelihood of households to substitute across different types of vehicles through a linear probability model.
- Then we aggregate our data at the postal code level to estimate the impacts on the spending on private vehicles.

# Automobile Purchases

| Dependent Variable: | Indicator for Four-Wheeler | Share of Four-Wheeler |
|---|---|---|
| | (1) | (2) |
| *Treated* × *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 |

- In Column (1), the probability that a registered vehicle is a four-wheeler decreases by 0.4% after subway expansions.
- In Column (2), subway expansions decrease the postal-code-level market share of four-wheelers by 1.2%.
- Explanation: households take non-four-wheelers from their home to the subway station, before relying on subway for long-distance travel.

# Automobile Purchases

| **Panel A: Vehicles Purchase** | | | | |
|---|---|---|---|---|
| Dependent Variable: | Non-Four-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: | Non-Four-Wheeler: High Quality | Non-Four-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 |

- Subway expansions reduce the demand for four-wheelers, the average cost of each vehicle, and total spending on automobiles.
- Results driven by low-quality four wheelers.
- Lower-income households who buy low-quality vehicles could improve their financial well-being as they buy less private vehicles.

# Additional Evidence of Heterogeneity by Income

| Dependent Variable: | Indicator for Delinquency (1) | Log(Delinquency Amount) (2) | Indicator for Prepayment (3) | Log(Prepayment Amount) (4) |
|---|---|---|---|---|
| *Treated* × *Post* | -0.0404** | -0.325* | 0.00986 | 0.0366 |
| | (0.0180) | (0.168) | (0.0116) | (0.123) |
| *Treated* × *Post* × $\mathbb{1}$(lowest-income) | -0.0128 | -0.110 | -0.00154 | 0.118 |
| | (0.0242) | (0.193) | (0.0231) | (0.267) |
| *Treated* × *Post* × $\mathbb{1}$(lower-middle-income) | -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 |

- Lower-middle-income households are more likely to replace private vehicle use with subway transportation, enhancing their financial flexibility.
- Lowest-income households, who likely could not afford private vehicles prior to the subway expansions, do not benefit from reduced vehicle expenditures.

# Alternative Explanation - Individual Income

1. Subway $\Longrightarrow$ Higher productivity $\Longrightarrow$ Higher income
   - The salaries for jobs in private firms are more performance-related.
   - If this channel holds, subway expansions should benefit individuals with jobs in the private sector more.
   - Compare residents who work in the public sector with those who work for private companies.

2. Subway $\Longrightarrow$ Higher participation rate $\Longrightarrow$ Higher income
   - Females have lower labor participation rate.
   - If this channel holds, females should be better off, relative to males.
   - Test this channel according to the heterogeneous effects by gender.

# Alternative Explanation - Individual Income

| **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 |

# Alternative Explanation - Macroeconomic Conditions

- The areas with subway expansions may grow fast relative to other areas $\implies$ better mortgage performance.

| Dependent Variable: | Annual Income (1) | Log(Annual Income) (2) | House Value (3) | Log(House Value) (4) | Loan Amount (5) | Log(Loan Amount) (6) |
|---|---|---|---|---|---|---|
| *Treated* × *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 |

- No evidence supporting this channel

# Alternative Explanation - Macroeconomic Conditions

- Higher loan to value (LTV) ratio $\implies$ higher risk of negative equity $\implies$ strategic defaulters.
- Suppose our results are driven by increasing house value, we should expect high LTV households become less delinquent.

| 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 |

# Robustness Checks

## Full Sample

| Dependent Variable: | Indicator for Delinquency | Log(Delinquency Amount) | Indicator for Prepayment | Log(Prepayment Amount) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Treated* × *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 |

## Fixed Postal Code Effects

| Dependent Variable: | Indicator for Delinquency | Log(Delinquency Amount) | Indicator for Prepayment | Log(Prepayment Amount) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Treated* × *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 |

# Robustness Checks

## Placebo Test

- Examine data from three years prior to the actual expansions.

| 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 |

# Robustness Checks

- The Indian interest rates exhibited a downward trend.
- Even though we control for time-fixed effects, we are concerned about the different responses to interest rate changes across postal code areas.
- We consider the sub-sample with households whose mortgage interest rates are floating.

| Dependent Variable: | Indicator for Delinquency (1) | Log(Delinquency Amount) (2) | Indicator for Prepayment (3) | Log(Prepayment Amount) (4) |
|---|---|---|---|---|
| *Treated* × *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 |

# Policy Implications

- We estimate the reduction in default rate as:

$$\Delta P(\text{Default}) = \Delta P(\text{Delinquency}) \times P(\text{Default}|\text{Delinquency})$$

- From February 2020 data: $P(\text{Default}|\text{Delinquency}) = 0.019$
- Estimated drop in delinquency: $\Delta P(\text{Delinquency}) = 0.0442$
- Implied drop in default rate: $0.0442 \times 0.019 \approx \mathbf{0.08\%}$
- Among 9,681 mortgages in Delhi, 72 (0.74%) defaulted.

Hence, subway expansions reduce default risk by approximately **11%** relative.

# Conclusion


- The opening of a new subway station decreases the mortgage delinquency rate and increases the prepayment rate in the same postal code.
- The effect attenuates when we move further away from the subway station.
- Our results are driven by reduced reliance on automobiles. Households are able to enjoy cost savings by spending less on transportation.

# Additional Tables

Table: Summary Statistics - Vehicle (Postal Code Level)

| | Full Sample | | | Control | | | Treatment | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | St.Dev. | Obs. | Mean | St.Dev. | Obs. | Mean | St.Dev. |
| **Variable** | | | | | | | | | |
| Non-Four-Wheeler | 5,722 | 415 | 490 | 3,303 | 337 | 412 | 2,419 | 512 | 563 |
| Non-Four-Wheeler (High Quality) | 5,722 | 85 | 102 | 3,303 | 70 | 87 | 2,419 | 106 | 117 |
| Non-Four-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*: Table reports means and standard deviations using the full sample, sample in the postal codes without subway expansions (Control), and sample in the postal codes with subway expansions (Treatment) from April 2015 to February 2020. Variables are the monthly registration number of non-four-wheeler, four-wheeler, logarithmic average spending on each vehicle, and logarithmic total spending on vehicles at postal code level. 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.

# Additional Tables

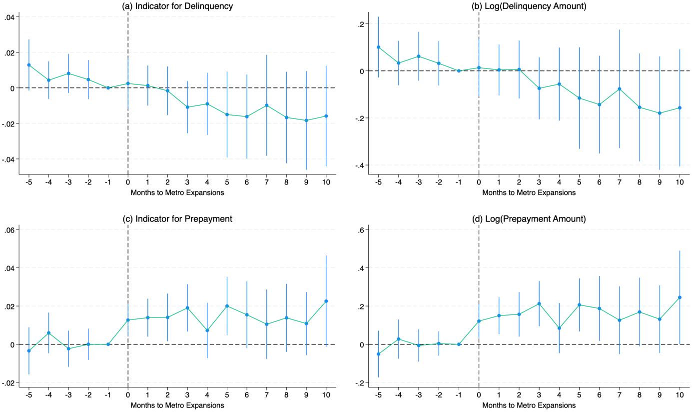
Table: Robustness Check - Inverse Hyperbolic Sine Function

| 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 co-variate, *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.

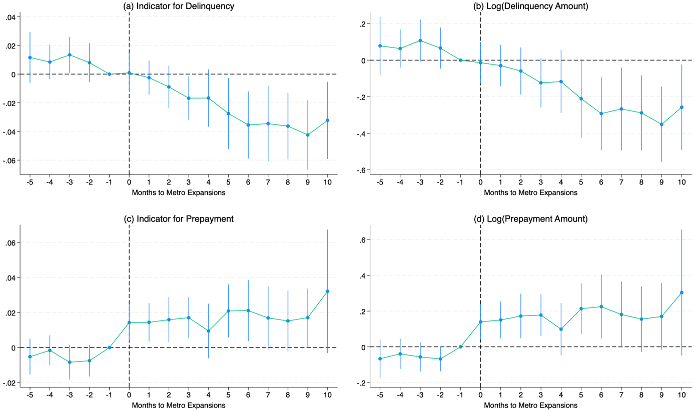
# Additional Figures

## Event Study of Subway Expansions - Close Postal Code Areas



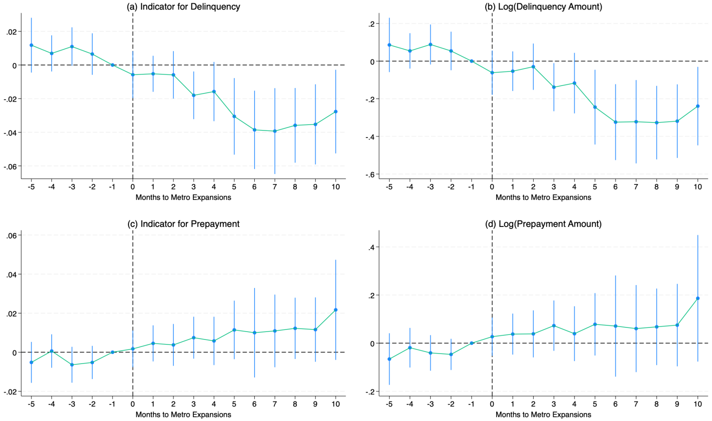
# Additional Figures

## Event Study of Subway Expansions - Far Postal Code Areas



# Additional Figures

## Robustness Check - Full Sample



# Additional Figures

## Robustness Check - Fix Postal Code Effects