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Road to Stock Market Participation

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Abstract

We study the impact of a national road construction program that brought access to previously unconnected pincodes in India, on stock market participation. Using a unique dataset on the trading behavior of over 13 million individuals, we find that construction of new feeder roads to a pincode increases the number of new investors by 6.8% and the number of trades by 7.9% and the effects are larger for rural vs. urban areas and for pincodes at intermediate levels of development. The stock market participation effects are largely driven by new bank branch openings within three years of the road construction suggesting a financial inclusion channel. We also see greater effects for pincodes more distant from the nearest big city, greater portfolio diversification, and increased trading in companies located farther away, all suggesting an information channel.

JEL Classification: O12, O16, O18, D8, G21

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Introduction

An extensive literature has documented the role of financial markets in economic development (Levine [2005] provides a review).¹ And yet stock market participation rates vary widely with the income level across countries (e.g. Guiso et al. [2003]; Giannetti and Koskinen [2010]). The low participation rates in developing countries is particularly puzzling given that developing country households are known to consume less and save more than those in developed countries (Modigliani and Cao [2004]). Understanding the underlying determinants of stock market participation has implications for both the consumption and risk behaviors of households and for aggregate macroeconomic effects.²

In this paper, we examine how stock market participation is influenced by infrastructure development, specifically by the construction of feeder roads that connect rural areas. We use comprehensive data on stock trading activity on the National Stock Exchange (NSE) of India by over 13 million individuals/households. The data includes information on the exact pincode location of each trader (or investor), trader demographics such as age and gender, and the specific stocks traded from 2004 to 2015. Using this data, we examine the change in stock market participation around a shock to the rural road network over this period arising from a national rural road-building program (the Pradhan Mantri Gram Sadak Yojana or Prime Minister's Village Road Program, or PMGSY) that connected previously unconnected roads.

A-priori it is not clear that infrastructure improvements should lead to increased stock market activity. The evidence on benefits of improved road connectivity in India is mixed with some studies showing large financing responses to road connectivity (e.g. Agarwal et al. [2021]), while others pointing to limited economic development from improved connectivity (e.g. Asher and Novosad [2020]) and inefficiencies in rural financial markets (e.g. Agarwal et al. [2017]). There are at least two broad channels through which road construction might influence stock market participation. The first is a financial inclusion channel whereby roads bring in greater access

¹Also see Levine and Zervos [1998], Demirgüç-Kunt and Levine [1996], Beck and Levine [2004], and Brown et al. [2009].

²Limited stock market participation has been shown to have a direct effect on the equity premium (Mankiw and Zeldes [1991], Heaton and Lucas [1999], Vissing-Jørgensen [1999], Brav et al. [2002]); diversification discount, market liquidity, and market crashes (see Basak and Cuoco [1998] and Huang and Wang [2009]). Also see Guiso and Sodini [2013] for a review of this literature.

to financing. Specifically, in the Indian context, new roads allow for opening up of new bank branches that allow for new investors to open trading accounts (also called "Dematerialized or Demat" accounts). The second is an information channel whereby with increased connectivity, there is greater awareness of investing in the stock market (e.g. [Hong et al. \[2004\]](#), [Guiso and Jappelli \[2005\]](#)).³

Our empirical setting offers us several advantages to test the role of infrastructure on stock market participation. First, unlike previous studies where stock market participation is determined from surveys, we can accurately measure the changes in stock market participation over time. Second, we are able to address concerns about the non-random nature of road placement by using the differential timing of road completion in each pincode, and comparing stock market participation in pincodes before and after a road is built, controlling for differences between pincodes that receive roads in different years. Finally, comprehensive data on the universe of bank branch openings from the Reserve Bank of India allows us to test the financial inclusion channel.

We see a significant increase in stock market participation associated with building of new feeder roads. In pincodes that received a new road under the PMGSY program, there is a 3.8% increase in the number of investors and a 6.2% increase in the total number of trades in that pincode-month. Most of these effects are driven by new investors (i.e. traders with less than three years trading experience) (6.8% increase in new investors and 7.9% increase in trades by new investors) and are economically significant, translating into 3 new investors and 41 additional trades per month. While these effects are largest within the first year of road construction, we still see positive and significant (though diminished) long-run effects of roads on stock market participation up to five years. These results are robust to a number of robustness checks including using state-year fixed effects, balanced sample regressions, and placebo tests where on randomizing the road completion date, we find no impact of road construction on stock market participation.

Next, we find substantial heterogeneity in the impact of road construction across different subsamples of investors. First, we find greater stock market participation among male investors and mature investors (over the ages of 55) after improved road connectivity than female investors and

³In a survey of households in rural and urban India, [NCAER \[2011\]](#) report inadequate information to be a key factor for low rate of stock market participation. The survey also points out that households in villages that are close to urban centers have higher participation rates than households in remote villages.

younger investors respectively. This is consistent with prior literature that documents that men trade more than women (e.g. Barber and Odean [2001]) and stock market participation peaks in the middle-age group (e.g. Van Rooij et al. [2011]). Second, across geographies, we see that new road construction mainly benefits investors in rural pincodes. In rural pincodes, increased road connectivity leads to 62.3% increase in trades and 33.1% increase in investors compared to urban pincodes. When we look at pincodes at different levels of economic development, we find that its not investors in the poorest regions (as measured by consumption per capita) but those in areas at intermediate levels of economic development that participate more actively in the stock market after road construction. These results are robust to using poverty rates as an alternate measure of economic development.

To better understand the mechanisms through which road construction affects stock market participation, we explore heterogeneity in the treatment effects. First, we find support for the information channel by showing that improved connectivity leads to increased stock market participation in more distant pincodes. The number of trades by new investors increases by 1.2% and the number of new investors increases by 0.6% for each additional 10kms between a pincode and the nearest metropolitan area. We also see that following new road construction, there is increased portfolio diversification with an increase of 4.7% in the number of unique tickers in the average portfolio. In addition, when we look at the type of stocks traded, we see that after new road construction in a pincode, investors are more likely to trade stocks of firms whose headquarters are located farther away from the pincode.

Second, consistent with the financial inclusion channel, we see that improved road connectivity in a pincode leads to greater stock market participation when there is a new bank branch opened in that pincode within three years after the road completion. Specifically, with the opening of a bank branch within a 3-year window after the road construction, there is a 15.6% increase in the number of trades by new investors and 13.4% increase in the number of new investors. We find larger effects for bank branch openings of state-owned banks compared to private banks. Given the greater outreach of public banks in India (e.g. Berger et al. [2008]), their role in financial stability and inspiring investor confidence, and lower fee-based incentives to encourage stock market trading, our results on public banks are suggestive of greater demand effects than supply effects.

To explore if the financial inclusion channel is benefiting only the marginal investor who experiences a positive wealth shock, we use rainfall shocks as a proxy for positive income shocks. We find no evidence that a positive wealth shock is moderating the impact of road construction on stock market participation in the pincode suggesting that the benefits of road construction is experienced widely.

To understand the source of the investment money, we look at the consumption and savings behavior of these households using more aggregate data. First, using a survey dataset of households at the district level (the Consumer Pyramids Household Survey data), we find a decline in consumption and increase in income in districts with new road construction. This provides suggestive evidence of capital re-allocation in households post new road construction from reduced consumption to increased investment. Second, using aggregate data on bank deposits, we find that after a pincode is connected by a PMGSY road, there is decline in deposits in the savings accounts in bank branches in that pincode suggesting again capital re-allocation from savings to the equity market.

Finally, we find no evidence that following new road construction, investors are taking on more risk and investing in high volatility stocks or that they are earning large monetary profits from stock market investing.

Overall, our paper shows a causal impact of improved road connectivity on stock market participation by Indian households via the information and financial inclusion channel.

Our findings contribute to the large literature documenting different factors responsible for stock market participation including fixed costs (e.g. [Vissing-Jorgensen \[2003\]](#)), financial literacy and household education (e.g. [Bernheim and Garrett \[1996\]](#), [Bayer et al. \[2009\]](#)), [Campbell \[2006\]](#), [Calvet et al. \[2007\]](#), [Christiansen et al. \[2008\]](#), [Van Rooij et al. \[2011\]](#)), social interaction and peer effects (e.g. [Madrian and Shea \[2001\]](#), [Duflo and Saez \[2002\]](#) and [Hong et al. \[2005\]](#)), lack of stock market awareness ([Hong et al. \[2004\]](#), [Guiso and Jappelli \[2005\]](#), [Brown et al. \[2008\]](#)), IQ stanine (e.g. [Grinblatt et al. \[2011\]](#)) and lack of trust ([Guiso et al. \[2008\]](#)). Our paper advances a new mechanism - road infrastructure development - as a way of overcoming many of the factors that lead to low stock market participation. In addition, ours is one of the few papers to explore factors

that can affect stock market participation in a developing country.

Several papers have studied the effect of the PMGSY program on rural households examining the impact on schooling and educational attainment (e.g. Mukherjee [2012] and Adukia [2017]), labor reallocation out of agriculture (Asher and Novosad [2017]), productivity (e.g. Shamdasani [2021] and Aggarwal [2018]). Our paper is closely related to Agarwal et al. [2021] but is different from their paper both in the focus and the data used. The focus in their paper is to examine if rural road connectivity increases the probability of getting a loan. They study financing responses to road connectivity in just two of the states in India (Odisha and Uttarakhand) and use loan level data from a single lender. Our focus on the other hand is to examine if rural road connectivity leads to increased stock market participation and if one of the channels through which this occurs is through road connectivity leading to the opening of more bank branches. Our data is also more comprehensive since we are looking at rural road construction under PMGSY in the whole country and have detailed information on the opening of all bank branches in the country.

1 Data and Summary Statistics

1.1 NSE Trading Data

We use comprehensive data on the universe of individual investors' daily trading activity compiled by the National Stock Exchange of India (NSE)⁴ over the period 2004 to 2017. For each trade, we have the key elements of a stock transaction including the date of the transaction, account type, tickers traded, the number of shares purchased or sold, and the execution price. Based on the account identifiers, 97% of the accounts are individual investor accounts and the remaining 3% are institutional investors. We restrict our sample to individual investor accounts and to trading of domestic stocks. Thus, we exclude all trading activity on ETFs and stocks issued by Non-Indian public firms.

The NSE data also contains demographic details on the investors including each investors gender, age, and pincode location. We match the pincodes in the NSE dataset to the official list of

⁴The National Stock Exchange of India is the leading stock exchange of India with 86% market share. According to the 2018 World Federation of Exchanges Report, it is the world's 11th largest stock exchange.

19,252 pincodes published by the Indian government.⁵ For observations which do not have a pincode directly listed in the NSE data, we replace their pincode with the most common pincode in the city they located.⁶

Overall, we have trading information for 13,510,473 unique investors located in 19,192 unique pincodes. Table A2 in the Appendix shows the geographical distribution of investors across all the states in India. We see that nearly one fifth of the investors in our sample are located in the state of Maharashtra, whose capital city Mumbai is home to the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) and since historically been the center of economic activity. Five other states including Gujarat, Tamil Nadu, West Bengal, Karnataka, and Uttar Pradesh account for another 42% of the sample.

All our analysis is at the pincode-month level. Thus, to measure stock market participation, we construct the following two variables: *Number of Trades* defined as the natural log of 1 plus the total number of trades in that pincode in a particular year-month; *Number of investors* defined as the natural log of 1 plus the total number of active investors in that pincode in a particular year-month.

To measure the extent of portfolio diversification in a pincode, we construct the variable *Number of Tickers* defined as the natural log of 1 plus the total number of tickers traded in a pincode in a particular month. We also calculate the monthly volatility of each stock and recognize a stock as a *High Volatility Stock* in a particular year-month if its price volatility is above the sample median for all stocks in the same year-month. We drop the top and bottom 1% outliers to eliminate the influence of outliers. Table 1 presents the summary statistics on each of the variables described above. The average number of trades in a pincode in a month is 757 trades though the range is from 1 trade in rural pincodes such as 212206 (a rural area in Kaushambi District, Uttar Pradesh) and 816118 (a rural area in Dumka District, Jharkhand) to 16,669 trades in metro areas such as

⁵The official list of pincodes corresponding to post offices published by the Government of India is available at <https://data.gov.in/catalog/all-india-pincode-directory>. The NSE dataset provides data at the sub-post office level and has 78,647 unique 6-digit pincodes which we then match up to the 19,252 pincodes in the official pincode list.

⁶For instance, the most common pincode for the city of Bangalore in our sample is 560078. We therefore assign the pincode 560078 to all investors in Bangalore whose exact pincode is unknown. We are able to assign pincode to 113,230 investors using this method (about 1% of the entire sample). All our results hold if we were to instead drop the observations with missing pincode.

400055 (Mumbai, Maharashtra) and 388009 (Ahmedabad, Gujarat). There are an average of 46 active investors and 98 stock tickers being traded in a pincode-month. Table A1 in the Appendix provides a detailed description of all the variables and Table A2 show the state-wise breakdown of all investors.

To explore the heterogeneity among the investors, we construct the following variables, again aggregated at the pincode year-month level: Using account opening date, we define *New Investors* as investors who opened trading accounts within the last three years and *Experienced Investors* as those who have had a trading account for more than 3 years. On the basis of age, we categorize the investors into three groups: *Young* (18-30 years), *Middle age*(30-55 years), and *Mature*(55+ years). We also separate the investors by gender into *Male* and *Female* investors. As seen in Table 1, across our sample, 63.1% of the investors are new investors. The majority are middle-age investors (53.3%) followed by young (24.6%) and mature investors (22.1%). Most of the investors are male (91.2%).⁷ We then calculate our trading variables, *Number of Trades* and *Number of Investors* in each of the identified demographic groups.

To obtain information on the firms being traded, we merge the tickers in the NSE data to those in Prowess, a database of provided by the Center for Monitoring the Indian Economy (CMIE). Prowess provides detailed financial information on public and private companies including the address of the headquarter location. For each of the public companies in an investor’s portfolio, we define *Distance* to be the distance between the geocode location (or latitude/longitude coordinates)⁸ of the investor and the public company.⁹

Figure 1 plots the geocodes of all the investors in the NSE sample (blue dots), and the publicly listed companies that they invest in (black dots). Based on the *Distance* measure, we look at

⁷For 5.1% of the investors in our sample the gender is not specified.

⁸The geocode coordinates are calculated for the center of the pincode. To obtain geocodes, we use *LocationIQ*, a commercial Application Programming Interface (API) that uses location identifiers such as state, district, and city to provide latitude/longitude coordinates. We supplement this with *GeoNames* (<https://www.geonames.org/about.html>), an open source database that provides latitude/longitude coordinates for pincodes around the world. While GeoNames is continually updated, the bulk of our data download from GeoNames was done in October 2020.

⁹The distance is computed using the standard formula used in several studies including [Ivković and Weisbenner \[2005\]](#) and [Tian \[2011\]](#):

$$d(location_i, location_j) = \arccos\{\cos(lat_i) \cos(lat_j) \cos(lon_i) \cos(lon_j) + \cos(lat_i) \cos(lat_j) \sin(lon_i) \sin(lon_j) + \sin(lat_i) \sin(lon_i)\}R \quad (1)$$

where R denotes the radius of the Earth (3,963 statutory miles approximately).

investment in companies that are less than 50 kilometers away, 50-100 kilometers away, 100-500 kilometers away, and over kilometers away. Specifically, the average monthly number of trades among the representative investors ranges from 639 (for companies located over 500 kilometers away) to 9 (for companies less than 50 kilometers). The monthly average number of trades for companies 50-100 kilometers and 100-500 kilometers away are 10 and 99 respectively.

In addition to the variation in geographic location of the public companies, we also explore variation in the distance between investors and the nearest cities. For each pincode, based on the 2011 Census we calculate the distance to the nearest cities with population larger than 100,000 people (referred to as *Tier-1* towns by the Census) and 1 million people (referred to as *Metros* by the Census). All distances are computed between geocodes. As seen in Table 1, the average distance between investors' pincodes and a city with population more than 100,000 (1 million) is 45.7 Kms (140.5 Kms) respectively.

1.2 PMGSY Data

While India has one of the largest and densest road networks in the world, till the year 2000, around 30% of its population, or 300 million people, lacked access to all-weather roads. In 2000, the Government of India launched the Prime Minister's Village Road Program (Pradhan Mantri Gram Sadak Yojana or PMGSY) to build all-weather roads and improve rural connectivity to unconnected villages across India. By the end of 2014, the PMGSY program had successfully built or upgraded a road for over 115,000 villages connecting over 30 million households in nearby towns (see [Adukia et al. \[2020\]](#)). As discussed in [Adukia et al. \[2020\]](#) and [Asher and Novosad \[2020\]](#), the focus of the program was to build feeder roads that provide terminal connections between the broader transportation network and previously unconnected villages.

We obtain data on all new roads built under the PMGSY program from the SHRUG (Socio-economic High-resolution Rural-Urban Geographic) platform created by [Asher et al. \[2020\]](#). For each new road built under the program, we have the exact completion date (year-month), which is crucial for our identification strategy, and the village and geocode location.¹⁰

¹⁰The geographic unit targeted for road construction in the program was a habitation (cluster of population), which is the smallest rural administrative unit in India. As discussed in [Adukia et al. \[2020\]](#), many villages have only one

Since the trading data is at the pincode level, we assign the villages to pincodes based on their geocodes. Specifically, all the villages within a 5 kilometer radius from the center of a pincode are assigned to the pincode. By construction, one village can be assigned to multiple pincodes if it is located within the 5 kilometer boundary of several pincodes. Thus, we assume that a paved road built in these boundary villages will have equal effects on all the pincodes it is assigned to. Across all the pincodes of the NSE trading data, we find 8,390 pincodes with at least one paved road built within a 5 kilometer radius.

We further restrict our sample to all pincodes that did not receive a new PMGSY road prior to October 2004 but received a new road between October 2004 and February 2015. Thus, all the pincodes in our sample receive a new road at some point during the sample period. In the final sample for analysis, we have trading variables across 4,154 unique pincodes in India.¹¹ Figure 2 provides a map for the 4,154 pincodes (blue dots) and the corresponding villages (red dots) in our sample and shows that most of the new roads under this program was constructed in the northern part of India. We define dummy variable *Connect* to take the value one in the month of road completion and thereafter. *Connect* is defined for the earliest date when a new paved road is finished under the PMGSY program in any of the villages associated with a pincode. As shown in Table 1, 66.7% of the sample pincode-month observations have the *Connect* variable equal to 1.

1.3 Bank Branch Data

To analyze if the effect of road construction on stock market participation is through the financial inclusion channel, we use data on the opening of bank branches across the country. Specifically, we use confidential and proprietary bank branch level data from the Reserve Bank of India (RBI). For each bank branch location, we have information on the pincode and the opening date of the branch/office. For the 102,968 bank branches that opened across India between 2004 and 2018, we use the pincode information of each branch and match them to the pincodes in our NSE trading sample. Over our sample period, we have 23,919 bank branches that opened in 3,557 pincodes in

habitation and many habitations were pooled to the village level for the purposes of the program.

¹¹Out of the 8,390 pincodes, 3201 already had a new road under the PMGSY program before October 2004; 1022 pincodes have always been connected by a PMGSY road, and 13 pincodes were never connected by a PMGSY road during our sample period. All these pincodes are removed from the sample.

our sample. For pincodes in the NSE trading data that can not be matched with the bank branch opening data, we assume there is no new branch opening for these pincodes during our sample period.

Next, we focus on bank branches that open within a 36-month window after the road construction to isolate the effect of bank branch openings. *New Branch Dummy* is an indicator variable which takes the value 1 if a new bank branch is opened in the pincode within a 36-month window after the road construction under the PMGSY program in that pincode. *Number of New Branches* is the total number of new bank branches that open within the same 36-month window after the road construction under the PMGSY program within the pincode. Table 1 shows that 43.2% of the pincodes in our sample have at least one new bank branch open in the 36-month window after receiving the new road, and the average number of new branches is around one.¹² Our analysis is robust to using both 12-month and 24-month windows instead of 36-months.

We are also able to classify the bank branches into *State-owned branch* and *Private branch* based on ownership type.¹³ Each of these are dummy variables take the value 1 for the corresponding bank type and 0 otherwise. We also use the *Number of State-owned branches* and *Number of Private branches*.

1.4 Measures of Economic Development

To explore the heterogeneity across regions with different levels of economy development, we first separate the pincodes into rural and urban using the post office type of a pincode.¹⁴ As seen in Table 1, of the 4,154 pincodes in our sample, 3,293 pincodes (79.3% of the sample) belong to rural areas, while the rest of pincodes are in the urban areas.

In addition to identifying rural and urban areas, we also use *Consumption per capita* data

¹²1,811 pincodes out of 4,154 pincodes have at least one new bank branch opened within the 36-month window after the road construction.

¹³Public banks include the State Bank of India, all other nationalized banks and regional rural banks while private banks include all non-state owned banks including foreign banks.

¹⁴Post offices in India are classified into five categories by the Department of Posts: DO(Divisional office), GPO(General Post Office), HO(Head office), SO(Sub Office) and BO(Branch office). We consider a pincode as belonging to a rural area only if its post office type is BO. As a robustness check, we also use an alternate ranking of the pincodes based on population as used by the Indian Space Research Organization (ISRO) - Metro, Tier-1, Tier-2, and Tier-3 pincodes - and classify Tier-3 pincodes as rural. Our results are materially the same under this alternate ranking.

obtained from the SHRUG as our measure on the economic development level across different geographic areas.¹⁵ Since the *Consumption per capita* is defined at the village level in the original data, we use the weighted average across all the villages associated with the pincode, weighting by the inverse distance between the village and the pincode to obtain measures at the pincode level. We further split the pincodes in our sample into three major categories: *Developed*, where the values of the *Consumption per capita* are above the sample median; *Intermediate development* where the values of *Consumption per capita* fall between median and 10th percentile values of the sample, and *Least developed* where the values *Consumption per capita* are below 10th percentile value of the entire sample. Table 1 shows that the average pincode in our sample has consumption/capita of 16478.11 INRs (equivalent to 331.42 USD according to the average annual exchange rate of 49.72 INR/USD over our sample period 2004 to 2015).

1.5 Rainfall Data

Following a large literature that uses rainfall shocks to proxy for income shocks, we collect rainfall data from the the Center for Environmental Data Analysis (CEDA) Archive.¹⁶ The rainfall data is available at the monthly 0.5×0.5 geo-grid level. We assign the geo-grid to a pincode if the distance between the pincode and the center of the geo-grid is less than 30 kilometers.¹⁷ We then use the inverse of distance as weights and calculate the pincode level weighted average monthly rainfall.¹⁸

Following Jayachandran [2006], Kaur [2019] and Gupta [2020], we define a pincode-month observation to have a positive rainfall shock if the rainfall is above the 80th percentile for that pincode and calendar month across all sample years and a negative rainfall shock if the rainfall measure is below the 20th percentile for that pincode and calendar month across all sample years. Thus, the variable *Rainfall Shock* takes the value 1 for positive shocks, -1 for negative shocks, and 0 otherwise. Over our sample period, 13.9% of the pincode-month observations are classified as posi-

¹⁵A large literature in development economics has used Consumption per capita as a reasonable proxy for long-term income/wealth especially in low income countries (see Ravallion [1995], Hamilton [2003]). We also use *Poverty Rate* data from the Census as an alternate measure for regional economic development and find similar results.

¹⁶The rainfall data is publicly available from CEDA's website <http://archive.ceda.ac.uk/>

¹⁷Several studies suggest a radius of 30 Kms is optimal when estimating the regional rainfall using the Inverse Distance Weighting (IDW) method. See Chen and Liu [2012] and Noori et al. [2014] for instance.

¹⁸For instance, if geo-grids A, B, and C have been assigned to pincode 200022, and the distance from each geo-grid to pincode 200022 is 10 kilometers, 5 kilometers, and 25 kilometers respectively, the corresponding weights for geo-grids A, B, and C are 10/40, 5/40, and 25/40 respectively.

tive rainfall shocks, and 11.2% of the pincode-month observations are classified as negative rainfall shocks.

2 Empirical Strategy

To study the causal impact of roads on stock market participation, we follow the empirical strategy in Adukia et al. [2020]. Our main empirical specification is a panel fixed effects regression that exploits the timing of road construction, within the set of all pincodes that received new roads between October 2004 and February 2015 under the PMGSY program. The specific equation we estimate is:

$$\text{Log}(Y_{i,t}) = \beta \cdot \text{Connect}_{i,t} + \xi_i + \kappa_t + \varepsilon_{i,t} \quad (2)$$

where Y are the two main measures of stock market participation in pincode i in year-month t : *Number of Trades* and *Number of Investors*.

The main coefficient of interest is β , which measures the impact of a new road on pincode-level stock market participation. Every pincode in our sample has $\text{Connect}_{i,t} = 0$ in the first month of our sample and $\text{Connect}_{i,t} = 1$ in the last month of our sample. Pincode fixed effects, ξ_i , are used to capture other time invariant factors within the pincode, and to control for systematic differences between pincodes which received roads at different times. Month fixed effects, κ_t , captures any variation along time that might impact stock market trading. The standard errors are clustered at the pincode level to account for serial correlation in the dependent variable. In our baseline estimation, we use an unbalanced panel where pincode-months with no trading activities are excluded from the sample. However, we repeat these estimations using a balanced sample taking zero for the pincode-months with no trading activity and find similar results.

The crucial assumption in our setting is that in the absence of PMGSY, trading activities would have followed the same trajectory in pincodes that received a paved road in different years, after partialling out the pincode and time fixed effects. We test the time trends of the road effects

following a similar setting to equation (1):

$$\text{Log}(Y_{i,t}) = \sum_{k \in (-5,5)} \gamma_k \cdot D_k + \xi_i + \kappa_t + \varepsilon_{i,t} \quad (3)$$

where D_k are a series of indicator variables that take the value 1 in the k^{th} year relative to the construction of road for that pincode. For instance, $D_2 = 1$ indicates 2 years after the road construction for the pincode. Unlike the setting in equation (1) where all the variables are defined at the monthly level, we define the variables annually for analyzing the time trends. Since all the pincodes in our sample are eventually “treated”, as suggested by [Borusyak and Jaravel \[2017\]](#) and [Adukia et al. \[2020\]](#), (3) can only be estimated with two coefficients being omitted. We therefore, use the coefficients in the year before road construction ($k = -1$) and in the first year of this setting ($k = -5$) as our reference group.

To explore the heterogeneity among investors, we replace Y in the above equation with the same measure constructed for different sub-groups: *New/Experienced investors*, *Male/Female investors*, and *Young/Middle-age/Mature investors*. Next, we explore whether the effects vary across regions with different levels of economic development. We first interact the *Connect* dummy with a dummy for Rural/Urban (*Rural*) pincodes and estimate the following regression:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{Rural}_i + \xi_i + \kappa_t + \varepsilon_{i,t} \quad (4)$$

where $Y_{i,t}$ are the different measures of stock market participation as before. We then interact the *Connect* dummy with an indicator for different levels of economic development (*Developed* (omitted category), *Intermediate development*, and *Least Developed*) for the pincode as proxied by *Consumption per capita* and estimate the following regression:

$$\begin{aligned} \text{Log}(Y_{i,t}) = & \alpha \cdot \text{Connect}_{i,t} + \beta_1 \cdot \text{Connect}_{i,t} \times \text{Intermediate development}_i \\ & + \beta_2 \cdot \text{Connect}_{i,t} \times \text{Least developed}_i + \xi_i + \kappa_t + \varepsilon_{i,t} \quad (5) \end{aligned}$$

where *Intermediate developed* and *Least developed* are dummy variables that take the value 1 if the *Consumption per capita* values for the pincode is between sample median and 10th percentile, and

below 10th percentile of the sample respectively.

We then explore three channels through which road construction might affect stock market participation. First is the information channel wherein new road construction can lead to greater stock market investing by reducing the information asymmetry. A large literature has suggested that non-participation can be explained by moderate fixed costs related to entry and participation (e.g. [Haliassos and Bertaut \[1995\]](#), [Vissing-Jørgensen \[2002\]](#) [Vissing-Jørgensen \[2003\]](#)) which include the costs related to learning about stocks, and acquiring information. With increased connectivity via new road construction, investors in rural areas have easier and better access to “hard” information (e.g. better and more accurate information on companies’ operating conditions, profitability, and growth opportunities) which could increase local stock market participation. In addition, newly connected roads also enable the transmission of “soft” information (e.g. rumors, or stock trading activities from remote friends or family members) via increased social interactions, peer effects that have been shown to increase stock market participation (e.g. ([Hong et al. \[2004\]](#), [Guiso and Jappelli \[2005\]](#), and [Brown et al. \[2008\]](#))). To test the information channel, we perform three types of tests: First, we investigate if the effect of new road construction is larger for investors in pincodes that are more remote from larger metropolitan areas. We estimate a model similar to our baseline specification but change the $Y_{i,t}$ to be specific to companies located a certain distance away from the local pincode. Specifically, we use the following specification:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{Distance}_i + \xi_i + \kappa_t + \varepsilon_{i,t} \quad (6)$$

where Distance_i is a continuous variable (in 10km units) calculated as the shortest distance between the pincode location of the investor to the nearest city with population above 100,000 people (*Tier 1 cities*) and the nearest city with population over 1 million people (*Metros*).

Second, we examine if there is a greater degree of portfolio diversification upon new road construction. We use the main baseline specification but with *Number of Tickers* traded in the pincode i in month t for the dependent variable $Y_{i,t}$. Third, we explore if there is a larger number of trades in companies that are more distant. We use the same baseline specification as before but replace the dependent variable, *Number of trades*, with Number of trades in companies that are

located less than 50 kms away, 50-100 kms away, 100-500kms away, and over 500kms away.

An alternate channel through which roads allow for greater financial infrastructure in the local region and, thus, enabling greater stock market participation. Several recent studies including [Agarwal et al. \[2021\]](#) and [Das et al. \[2019\]](#) show that construction of new roads and road upgradation leads to increased financing to households, especially in rural areas, allowing them to make the best use of new productive opportunities. To isolate this, we examine the effect of new bank branch openings in the pincode within 36 months of the road completion date in the pincode. Specifically, we estimate the following equation:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{New Branch Dummy (or Number of New Branches)}_i + \xi_i + \kappa_t + \varepsilon_{i,t} \quad (7)$$

where $Y_{i,t}$ are the different measures of stock market participation as before.

There are several explanations for why we might expect bank branch openings after road construction to aid in stock market participation - first, it could be a simple enabling story where villagers are now able to open trading accounts with the bank;¹⁹ second it could be a demand side story where villagers reallocate capital from consumption to more productive uses via savings accounts in banks; or third it could be a supply side story where banks actively recommend stock market investments to newly connected villagers.

While we are open to all of these interpretations, we try to investigate more closely if we can separate out these mechanisms. Using data on bank ownership we explore if our results are driven by the opening of state-owned (or public) bank branches versus private bank branches. First, on the enabling mechanism, state-owned banks in India have been shown to have greater outreach (e.g. [Berger et al. \[2008\]](#)) than private banks. Second, a large literature on bank ownership shows that lending by state-owned banks is less pro-cyclical and hence they play a critical role in financial stability (see for example, [Brei and Schclarek \[2013\]](#), [Cull and Peria \[2013\]](#), [Bertay et al. \[2015\]](#), and [Bosshardt and Cerutti \[2020\]](#)) which in turn is suggestive of greater investor confidence in public banks. Both these explanations (enabling and greater demand) would suggest that we should

¹⁹The Securities and Exchange Board of India (SEBI) requires everyone who wants to trade Indian securities to have a demat account (or dematerialised account), which is an electronic record tracking ownership of tradable assets.

find stronger effects for state-owned banks than private banks. On the other hand, our sample is restricted to trading on individual stocks, while the investment products offered by banks are usually mutual funds, credit deposits and exchanged traded funds (ETFs). Therefore, it is less likely that bank financing advisors would recommend investors to buy individual stocks directly. Furthermore, there is some evidence suggesting that public banks earn less fee-based income and thus have less incentives in interest income from stock brokerage (e.g. [Pennathur et al. \[2012\]](#)). Hence if it is only the supply side channel, we should expect weaker effects for the opening of state-owned bank branches compared to private bank branches. Finally, in section 4.4 we use the household-level consumption data in several districts to analyze whether the completion of new roads leads to different consumption behaviors within households, which could help validate the demand side story.

Finally, we test whether the new investors post new road construction are marginal investors by looking at the effect of income shocks. While most studies predict a positive association between wealth and stock market participation, interpreting it as a financial participation cost (e.g. [Vissing-Jørgensen \[2003\]](#), [Calvet et al. \[2009\]](#), [Calvet and Sodini \[2014\]](#)), [Brunnermeier and Nagel \[2008\]](#) and [Andersen and Nielsen \[2011\]](#) find that sudden windfalls do not increase stock market participation. Households in rural India face high income volatility due to agricultural income being their main source of income, which in turn, is dependent on rainfall. Studies such as [Jayachandran \[2006\]](#), [Kaur \[2019\]](#) and [Gupta \[2020\]](#) have shown rainfall shocks to be a good proxy for local income shocks. Following this setting, we test the income shock channel using the equation:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \text{Rainfall Shock}_{i,t} + \gamma \text{Connect}_{i,t} \times \text{Rainfall Shock}_{i,t} + \xi_i + \kappa_t + \varepsilon_{i,t} \quad (8)$$

where $\text{Rainfall Shock}_{i,t}$ is the rainfall shock defined at the pincode-month level. If we find that the effects of new road construction are driven entirely by investors experiencing positive income shocks (positive and significant interaction term γ), then it would suggest that it is the fixed financing costs of participation that is driving stock market participation.

3 Results

3.1 Does Road Construction lead to Increased Stock Market Participation?

Table 2 reports the main results of the impact of roads on stock market participation. Columns 1 and 2 report the estimation results for all investors, columns 3 and 4 for new investors, and columns 5 and 6 for experienced investors. In the sample of all investors, the construction of a newly paved feeder road to a pincode leads to a 6.2% increase in the Number of Trades and 3.8% increase in the *Number of Investors* in that pincode-month. Economically, these effects translate to 47 additional trades and 2 more investors in each pincode for each month on average. These results are almost entirely driven by new investors. Construction of a newly paved new road leads to a 6.8% increase in the number of new investors and an 7.9% increase in stock trading by new investors while the number of trades by experienced investors goes up only marginally by 4.1% and the number of experienced investors decreases by 2.5%. Economically, the new road leads to 3 more new investors while reducing the number of experienced investors by 1, leading to a net change of 2 additional investors in the pincode and 41 additional trades by new investors.

Figure 3 shows the dynamic effects by plotting the coefficient estimates of the indicator variables described in equation (3). For each of the dependent variables, the coefficients become positive and significant only in the year of the road construction and thereafter, with the maximum effect in the first year after road construction. While the magnitude of the coefficients slightly diminish after the first year, they are still positive and significant suggesting long-run effects of roads on stock trading activities.

We next subject our baseline results to a number of robustness checks. First, we re-estimate our baseline model using state-year fixed effects to address the concern that time varying state level policies are driving both road construction and stock market participation. Second, we expand our unbalanced panel to a balanced panel by filling in zeroes when there are no trading activities in that pincode-month. Panel A of Table A3 in the Appendix reports results where we add the state-year fixed effects to our baseline model, and panel B of Table A3 in the Appendix reports results where we use the balanced panel sample. In both panels, columns 1 and 2 report the results

for all investors and columns 3 and 4 report the results for new investors. The coefficients of the *Connect* dummy variable are positive and significant in all specifications.²⁰

Finally, we run placebo regressions: First, we randomize the road completion date for all pincodes across the entire sample period in panel A of Table A4 of the Appendix. Second, we randomize the road completion date for all pincodes within the same month in panel B of Table A4 of the Appendix. For each setting, we run 500 samples and average the regression coefficients and standard errors across these 500 regressions. The placebo tests allow us to maintain the distribution of completed roads across pincodes while disrupting the completion date for road construction. Table A4 of the Appendix shows that the coefficients for *Connect* dummy are *not* economically and statistically different from zero. Overall, our robustness checks support the hypothesis that construction of new feeder roads has a positive impact on on stock market participation, especially for new investors.

Since the positive effects of roads on stock market participation are primarily driven by the new investors, going forward, all our results are based on trading activities of the new investors. However, tables for the full sample of investors are available in the Internet Appendix.

3.1.1 Heterogeneous Effects

Tables 3 and 4 report the heterogeneous effects on stock market participation among different demographic groups and across different regions respectively. Panel A of Table 3 shows that while construction of a new road is associated with increased stock market participation for both male and female investors, the economic effects are much larger for male investors. Economically, a new road construction in a pincode leads to 37 additional trades by male investors (compared to 4 by female investors) and 2 additional male investors (compared to 1 female investor) participating in the market. Panel B of Table 3 shows that a new paved road increases the number of trades by 8.6%, 8.3%, and 16.1% respectively among the young, mid-age and mature investors, which is economically equivalent to 9, 20, and 12 new trades by young, mid-age and mature investors respectively. We also see that largest increase in number of investors is among the mature investors

²⁰As an alternate robustness check, we also find our results to hold if we were to use a balanced sample with pincodes that have at least 12-months of data before and after the road completion.

(8.8%) followed by 6.2% for middle-age and 4.6% for young investors, which are economically one more investors for each age group. These results show that building of new roads impacts male and older investors, two groups who previous literature has shown to participate more in the stock market than females and younger investors (e.g. Barber and Odean [2001], Van Rooij et al. [2011], Constantinides et al. [2002]).

Table 4 shows the heterogeneous effects of roads on stock market participation across *Rural/urban* regions and regions with different levels of economic development. Columns 1 and 3 reports the results when we interact the *Connect* with a rural dummy, whereas columns 2 and 4 report the results when we interact *Connect* with indicator variables for economic development, *Developed* (omitted category), *Intermediate development*, and *Least developed*. We omit the main effect of the regions in these regressions since they are subsumed by the pincode fixed effects.

In columns 1 and 3, the coefficients for all the interaction terms are positive and significant, suggesting that the positive effects of roads on stock market participation are larger in rural areas compared to urban areas. When we look across different levels of economic development, we see that road construction has the greatest impact on stock market participation in areas with intermediate development - columns 2 and 4 show that the completion of the new road leads to 11.3%(8.4%) increase in trades and investors respectively in areas with intermediate development. The interaction of *Connect* and *Least Developed* is not statistically significant suggesting that compared to the developed regions, roads stimulate stock market participation in areas that are relatively less developed but not necessarily the least developed ones.²¹ In addition, we also plot the time trends of roads impacts across areas with different levels of development in Figure 4. Consistent with our regression results, the positive effects of roads on the different measures of stock market participation are largest for areas of intermediate economic development.²²

²¹In Appendix Table A5, we undertake robustness checks where we use an alternative definition of *Rural* variable (Tier-3 pincodes as identified by the Census), and *Poverty Rate* as the regional economic developed measure. The results are similar to the ones in Table 4.

²²A similar graph using *Poverty Rates* as the economic development measure is shown in Figure A1.

4 Mechanisms

In this section, we explore the possible underlying mechanisms through which road construction leads to increased stock market participation. In section 4.1, we test whether additional connectivity brought about by the new road construction both reduces information asymmetry and generates peer effects, leading to increased stock market participation, which we refer to as the *Information Channel*. In section 4.2, we explore whether completion of new roads leads to the improvement of financial infrastructure in the local region allowing for greater stock market participation, which we refer to as the *Financial Inclusion* channel.

4.1 The Information Channel

We report our results for the information channel in Table 5. Panel A of Table 5 examines if the effects of roads on stock market participation are larger for pincodes located further away from large metropolitan cities. The *Distance* measure (in 10km units) captures the shortest distance between the pincode with the new road construction and the nearest city with more than 100,000 people (Tier 1 city) and 1,000,000 people (Metro city) respectively. Columns 1 and 2 show the results for number of stock trades by new investors and columns 3 and 4 report results for the number of new investors. The results show that the benefits of new road construction on stock market participation are particularly strong for more distant pincodes, especially those that are farther away from metropolitan cities. The number of trades by new investors increases by 1.2% and the number of new investors increases by 0.6% for each additional 10kms between a pincode and the nearest metropolitan city with population more than 100,000 (1 million) people respectively.

An alternate test of the information channel is whether investors hold more diversified portfolios after the construction of the new road. Column 1 of panel B of Table 5 uses *Number of tickers* as an alternate dependent variable and shows that following the construction of a new feeder road to the pincode, the number of unique traded tickers increases by 4.7%, which is equivalent to an increase of 4 tickers among all new investors. In unreported results, we find these results to hold across different samples of investors, including male, female, young, mid-age, and mature investors.

In columns 2 to 5, we examine the effects of road construction on the number of distant stocks traded by examining the number of trades in public companies that are located less than 50 Kms, 50-100 Kms, 100-500 Kms, and more than 500 Kms away respectively from the pincode. The coefficients of the *Connect* dummy are positive and significant for all columns. The number of trades on public companies located less than 50 Kms, 50-100 Kms, 100-500 Kms and over 500 Kms away increases by 2.1%, 5.6%, 14.7% and 7.4% respectively after the completion of the new road.

4.2 The Financial Inclusion Channel

The results of the financial inclusion channel are reported in Table 6. Columns 1 and 2 in panel A of Table 6 report the results for *Number of Trades* by new investors and columns 3 and 4 report the results for *Number of Investors* (new investors). The coefficients for the interaction term on *Connect* and *New Branch dummy* are positive and significant in columns 1 and 3 suggesting that pincodes that had new bank branches open within three years of the road completion have 15.6% increase in stock trades, and 13.4% increase in the number of new investors participating in the stock market. Columns 2 and 4 also report significant results for the intensity of new branch openings. Each additional bank branch opened within three years of the road construction leads to 1.4% increase in stock trades and 2.2% increase in the number of new investors.

As discussed before, the opening of bank branches could result in decreased participation costs since banks allow for establishment of demat and trading accounts, making investing easy for the casual and beginner investor. It could also be a demand side story where clients who open bank accounts are able to reallocate capital from consumption to investing or a supply side story where banks actively recommend investing in individual stocks to clients. While we are unable to differentiate between these three channels, we try to make some progress by using information on the bank ownership type of the new branch opening. State-owned banks have greater outreach and are less likely to promote trading in individual stocks because of lower fee based income compared to private banks. So even if there are supply side effects at play, these should be less important for state-owned banks.

In panel B of Table 6, we interact *Connect* dummy with *State-owned branch* and *Number of*

state-owned branches Columns 1 to 4 report results for *Number of New Trades* and columns 5 to 8 report the results for *Number of New Investors*. We find the interaction of State ownership of the new bank branch and *Connect* dummy to be positive and significant suggesting that it is more likely the demand side effects rather than supply side effects driving stock market participation.

4.3 Is there a reallocation from consumption and saving to investment?

In this section, we explore if the financial inclusion channel is consistent with households having greater opportunities to reallocate capital from consumption and savings to more productive uses such as investment.

4.3.1 Allocation from consumption

While we don't have consumption data for individual investors, we try to shed some light on this using aggregate statistics at the district level from the CMIE Consumer Pyramid Household Survey (CPHS) data. CPHS are household surveys designed to capture household well-being in India with detailed information on income and expenditure patterns each month since January 2014. Thus, this data is available only for the last year of our sample period since the PMGSY data ends in February 2015. In addition, the CPHS data is at the district level, while the PMGSY data is at the village level. To take into account these two issues, we alter our empirical design in this section in the following ways: First, we only focus on districts that had PMGSY roads completed between January 2014 and December 2015 (so we allow for at least 10 months of consumption data after the last road completion). If a district had multiple roads completed during this time period, we use the earliest road completion date to identify pre-treated and post-treated groups. Second, we only include a district in our sample if the district does not have any roads in a continuous five-year window before the new road completion date. Third, similar to our NSE sample, we only include the household in our sample if they have records in both the pre-treated and post-treated period. These criteria provide a long enough window for the effects of any prior road construction to become steady, thereby allowing us to isolate the real effects of current roads on household income and consumption. The final CPHS sample contains 145,958 household-month observations

over 7,178 households across 16 districts over the 14 month period. For each household-month, we calculate the log transformation of the total income and total expenditure after removing outliers below the 1st percentile and above the 99th percentiles. On average, the representative household in the sample has income level of 8165.3 Indian Rupees (164.26 USD), and consumption level of 6789.17 Indian Rupees (136.58 USD).²³

To analyze the effects of roads on consumption behavior, we estimate the following equation:

$$Y_{h,t} = \beta \cdot \text{Connect}_{d,t}^{CPHS} + \eta_h + \kappa_t + \varepsilon_{h,t} \quad (9)$$

where Y are $\text{Log}(\text{Consumption})$ and $\text{Log}(\text{Income})$ which are the log values of household consumption and income for household h in month t . $\text{Connect}_{d,t}^{CPHS}$ is an indicator variable which equals to 1 if a district received a new PMGSY road between 2014 and 2015, and didn't receive any road during the past 5 years. η_h represents the household fixed effects. To identify heterogeneous effects of roads on consumption across households with different income levels, we interact the Connect^{CPHS} dummy with a dummy for *High Income* households where High Income households are defined based on whether the average household income is above the median, 75th, or 90th percentile of monthly household income in our sample.

Panel A of Table 7 shows that the completion of new roads leads to a decrease in average consumption while increasing the average household level income. These results provide suggestive evidence of capital re-allocation in households after the construction of a new paved road to that pincode. Panel B of Table 7 shows that high income households see greater declines in consumption and increases in income after the road construction. Overall, these results provide suggestive evidence of capital re-allocation in households after the construction of a new paved road to that pincode, especially in high income households.

4.3.2 Allocation from saving

To analyze whether there is an allocation of capital from savings in the bank to the equity market, we use the bank deposit data from the RBI-Basic Statistical Return (BSR) dataset. The RBI-BSR

²³We use an average annual exchange rate of 49.71 INR/USD over our sample period 2004 to 2015.

data reports annual deposit information in every branch of every scheduled commercial bank in India. For each branch-year, we have information on deposits in the current account (business account), savings account and term account, as well as the aggregate amount of deposit. We focus our analysis on the deposits by individuals rather than other type of depositors.

We restrict the RBI-BSR sample to 919,034 branches across India whose location information is available during 2004-2015. Further, we narrow our sample to branches that are located in the 4,154 pincodes that are part of our main analysis. This yields 161,422 branch-year observations across 23,580 bank branches over 3512 pincodes between 2004 and 2015.²⁴ After removing outliers, the sample average deposit in the current, saving, and term account is 10634.85, 118609.2, and 135471.1 Indian Rupees respectively.

We use the following equation to estimate the effects of roads on savings:

$$Deposit_{b,i,t} = \beta \cdot Connect_{i,t} + \phi_b + \kappa_t + \varepsilon_{b,t} \quad (10)$$

where $Deposit_{b,t}$ is the log value of total amount of deposit in each type of account for individual depositors in branch b . $Connect_{i,t}$ is an indicator variable which equals 1 if the pincode i , where branch b is located, received a new PMGSY road in year t and thereafter. ϕ_b and κ_t represents the branch and year fixed effects. If investors were to indeed move capital from the savings account to the equity market after the road construction, we should observe declines in bank deposits, especially in the savings account, after the pincodes are connected by new roads.

The effects of improved road connectivity on bank deposits are reported in Table 8. Cols 1-3 report results for each of the three accounts and col 4 reports results for aggregate deposits. The coefficients are statistical insignificant for current account and term account, but negative and significant for savings deposits and aggregate deposits. These results suggest the re-allocation of capital from bank deposits to the stock market, providing another supporting evidence on the financial inclusion channel.

²⁴There are 642 pincodes do not have any branches located in.

4.4 Do roads benefit only the marginal investor?

In this section, we examine if the effects of roads on stock market participation through the financial inclusion channel is only for the marginal investor experiencing a positive wealth shock, as proxied by a positive rainfall shock. Before we conduct our regression analysis, we first investigate if there is any seasonality in terms of trading activities across one year. For each month, we plot the average distribution of *Number of New Trades* and *Number of New Investors* across all the pincodes in our sample in Figure 5. The monthly average values for both *Number of New Trades* and *Number of New Investors* are consistent across all the months in a year, indicating there is no seasonality for the trading activities among investors.

Table 9 reports the regression results where we use the concurrent rainfall shock and 1-month lagged rainfall shock interacted with *Connect* dummy. The coefficients of the interaction terms for the *Number of New Trades* are negative but statistically insignificant. When we look at *Number of New Investors*, the interaction of *Connect* x *Rainfall Shock* is negative and significant, suggesting that with improved road connectivity a positive income shock is not associated with greater number of new investors participating in the market though the overall effect of *Connect* is still positive and significant. Overall, these results show that it is not the case that the financial inclusion channel is driven only by investors who experience a positive income shock.

5 Monetary Profits & Risk-Taking

In this section, we investigate whether the construction of new roads have implications for the risk-taking by investors and monetary profits. Following Barber et al. [2009], we calculate the buy-and-hold monetary profits by calculating the net change on stock holding by investors.²⁵ For instance, if an investor buys 1000 shares of company A on Jan 1st, 2012 and sells 600 shares on company A on the same day, we calculate the investor's net holding change of company A as 400 shares, and code it as a *net buy* for the day. If the number of shares sold is larger than the number of shares bought, we code it as a *net sell*. The purchase price of the stock is then calculated as

²⁵According to Barber et al. [2009], calculating monetary profits offers more precise accounting for gains and losses from trades.

the difference between the buy value and sell value divided by net shares bought. We assume that investors hold the stocks for a fixed period of time and consider different time windows - namely 1, 10, 25, 140 trading days. For each stock, for *net buy* activity on day t , we calculate the monetary profits for holding period X (where $X = 1, 10, 25,$ and 140) days using the formula:

$$\text{Profits}_t^{\text{Net Buy}} = \text{Net Buy Value}_t \times \frac{\text{Price}(t + X) - \text{Price}(t)}{\text{Price}(t)}$$

Analogously, the monetary profits from a *net sell* can be calculated using the formula:

$$\text{Profits}_t^{\text{Net Sell}} = \text{Net Sell Value}_t \times \frac{\text{Price}(t) - \text{Price}(t + X)}{\text{Price}(t)}$$

After calculating the monetary buy-and-hold profits for each stock traded, we aggregate the data from investor-stock-day level to investor-month level and calculate the aggregate investors' monetary profits across all trading activities in a month. Finally, we take average monetary profits for all investors in a pincode-month.

To examine if new road construction changes the risk taking profile of investors, we use the number of trades in high volatility stocks as a proxy for risk-taking activities. For each stock, we calculate its monthly price volatility and recognize it as a high volatility stock if its price volatility is above the sample median for all stocks in the same month. As a proxy for risk-taking, for each pincode-month we count the total number of trades in high volatility stocks in the previous month.

We use a similar set of specifications as our baseline setting replacing the dependent variable with *Monetary Profits* and *Number of Trades in High Volatility Stocks* in Table 10. Columns 1-4 report the results for monetary profits for different holding periods, and column 5 shows the result for stock trades in high volatility stocks. The *Connect* dummy is insignificant for all columns and there is no significant effect of *Connect* dummy on trading of high volatility stocks.

Overall, our results in this section suggest that the new road construction is not altering the risk taking behavior of the investors and there is little evidence that these investors are making huge monetary profits from investing in the stock market.

6 Conclusion

A long standing finance and growth literature has argued for the case of a well developed stock market with broad participation as one of the channels of ushering economic growth. However, low stock market participation has been a long standing puzzle especially for a fast growing developing country like India with a high savings rate. In this paper, we advance a novel mechanism that affects stock market participation rates - improvement of physical infrastructure. Using a unique data set on stock trading activities of over 13 million households in India between 2004 and 2015, and a national rural road building program, we find that construction of new feeder roads increases stock market participation, especially for new, inexperienced investors in rural areas of intermediate levels of economic development.

We find support for two channels underlying the positive effects of roads on stock market participation: the information channel and the financial inclusion channel. First, we show that construction of new roads leads to greater stock market participation for more remote pincodes. There is also greater portfolio diversification, and a reduction in home bias (greater trading in stocks that are more distant), all suggesting that infrastructure improvements lead to a reduction in information asymmetry, allowing for greater stock market participation. Second, we show that increased stock market participation following new road construction is particularly high in areas where there is a new bank branch opening, especially new state-owned bank branches, within three years of the road construction. We have suggestive evidence that there is a decrease in consumption and saving, while increase in investment in districts with new road constructions. We also find that it is not just the marginal investor benefiting from a positive wealth shock that is participating in the market following road construction. Together, these effects suggest a financial inclusion channel where new bank branches following road construction allow for opening of trading accounts as well as better saving decisions, allowing for greater stock market participation. We find little evidence that investors earn more monetary profits or become more risk-taking after new road construction.

Overall, our paper has important implications for household welfare through stock market participation. If wider stock ownership is a policy reform agenda for developing countries, our paper suggests that improving physical infrastructure addresses the twin problems of financial

access and inadequate information, allowing for better integration of investors in remote and rural areas.

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Annette Vissing-Jørgensen. Perspectives on behavioral finance: Does "irrationality" disappear with wealth? evidence from expectations and actions. *NBER Macroeconomics Annual*, 18:139–194, 2003.

Figure 1: Geographic Distribution of Pincodes and Indian Public Listed Companies

This map plot the geographic distribution of investors in our NSE sample and all public Indian companies from Prowess. The blue dots represents the pincode for investors in the NSE data, while black dots represents the location of Indian public companies.

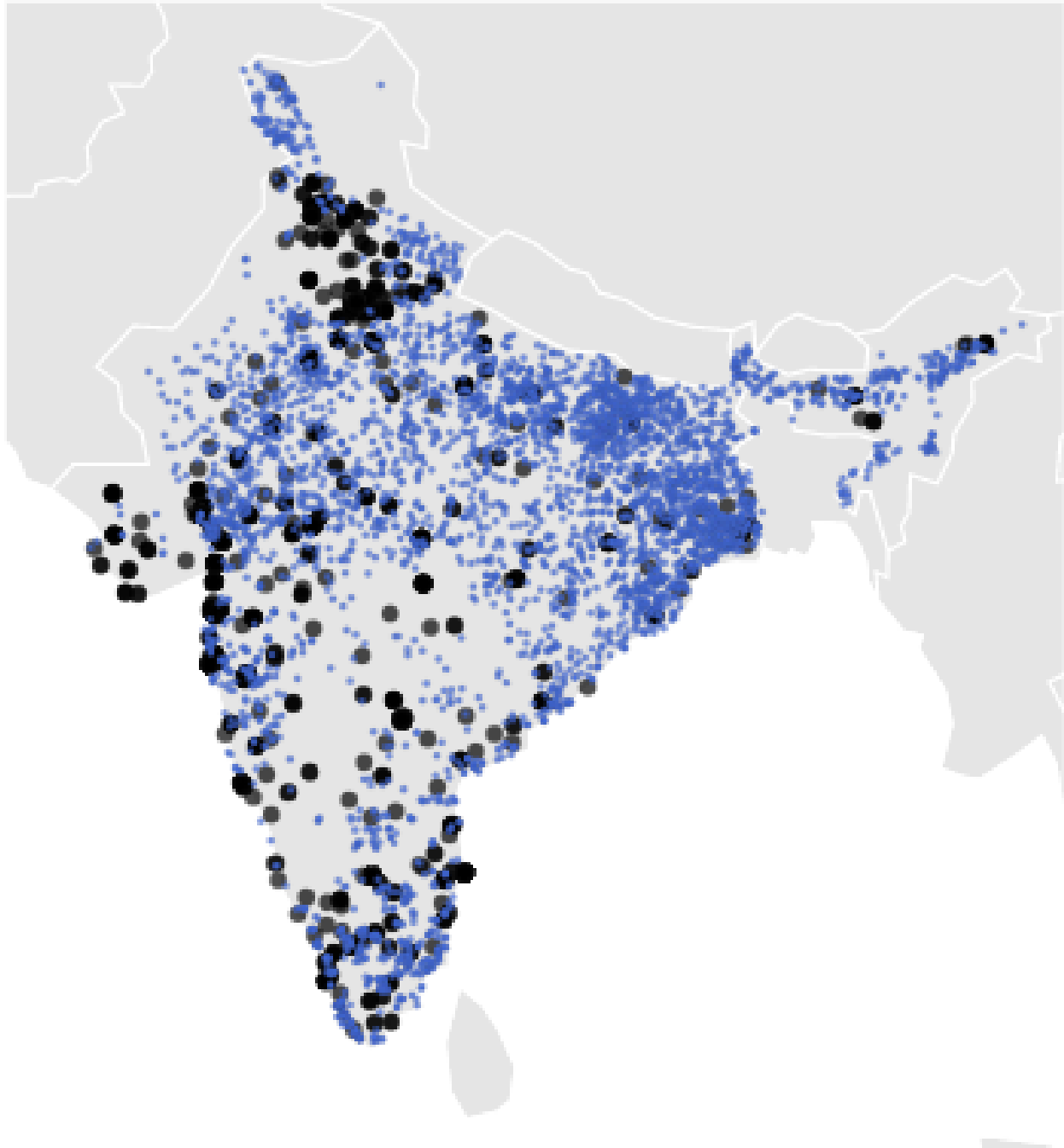


Figure 2: Geographic Distribution of Villages and Pincodes in our Sample

This map plot the geographic distribution of investors in our NSE sample and all villages in the PYGSY data. The blue dots represents the pincode for investors in the NSE data, while red dots represents the village within 5 Kms radius for each pincode.

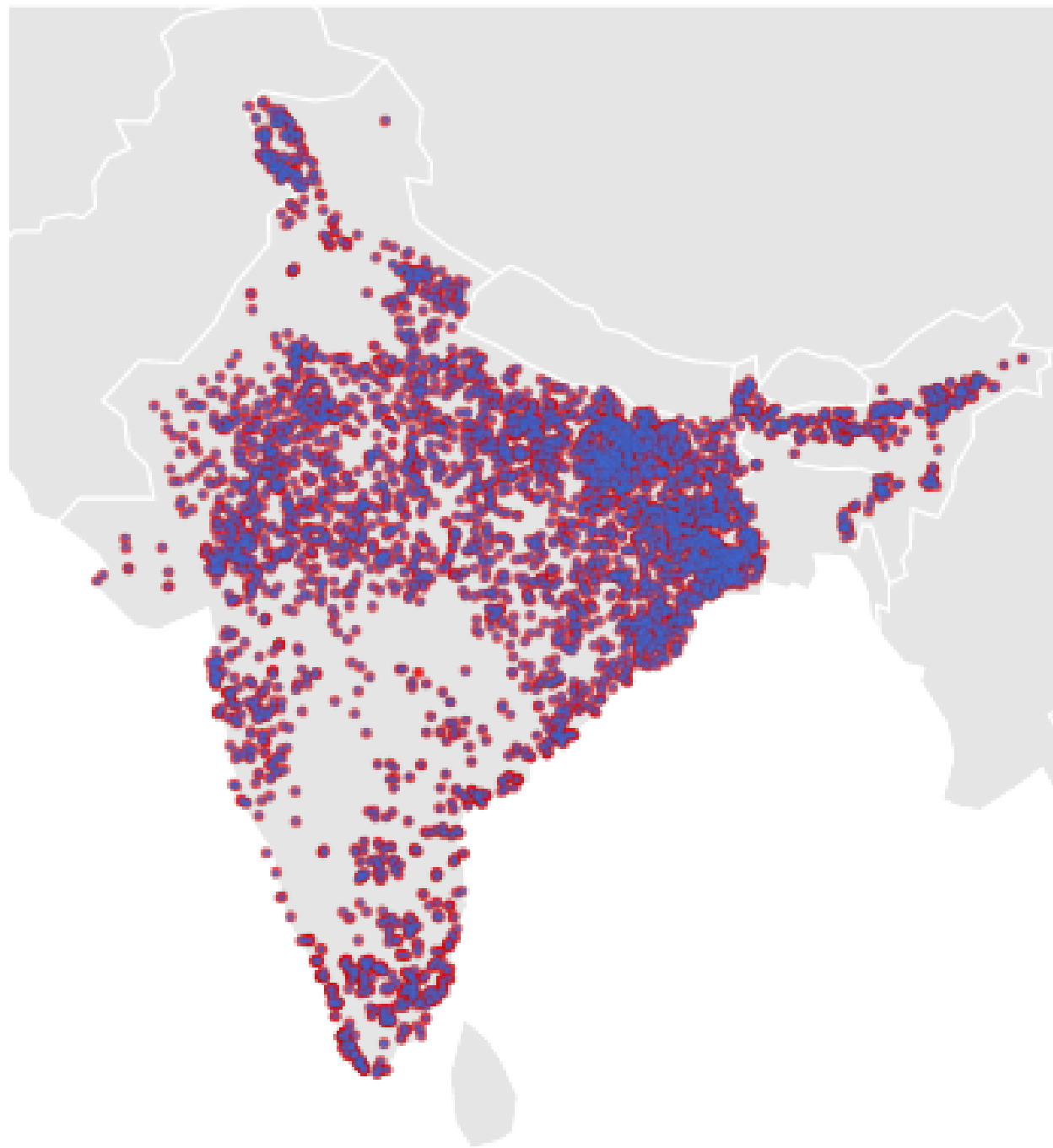


Figure 3: Time Trends of Road Impacts on Stock Tradings

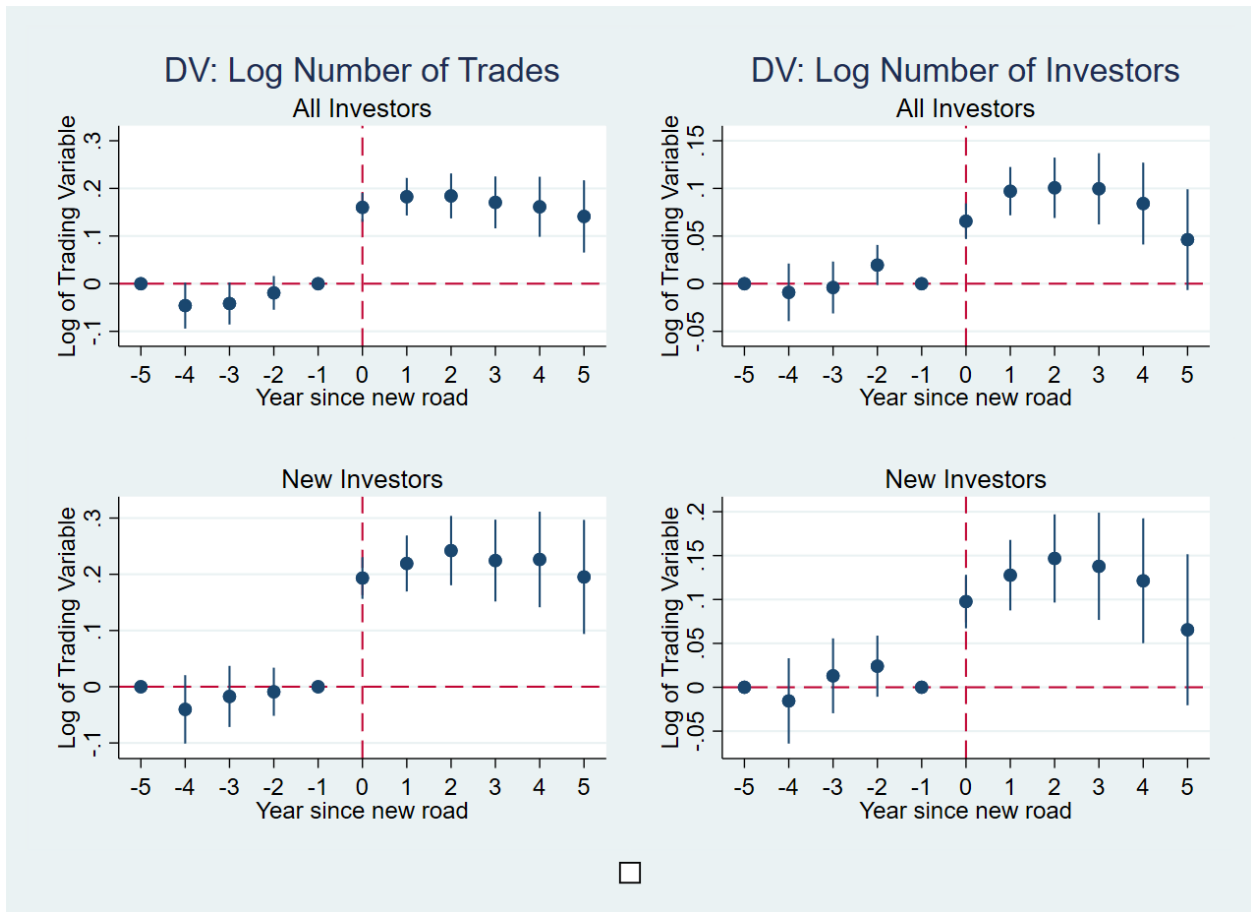
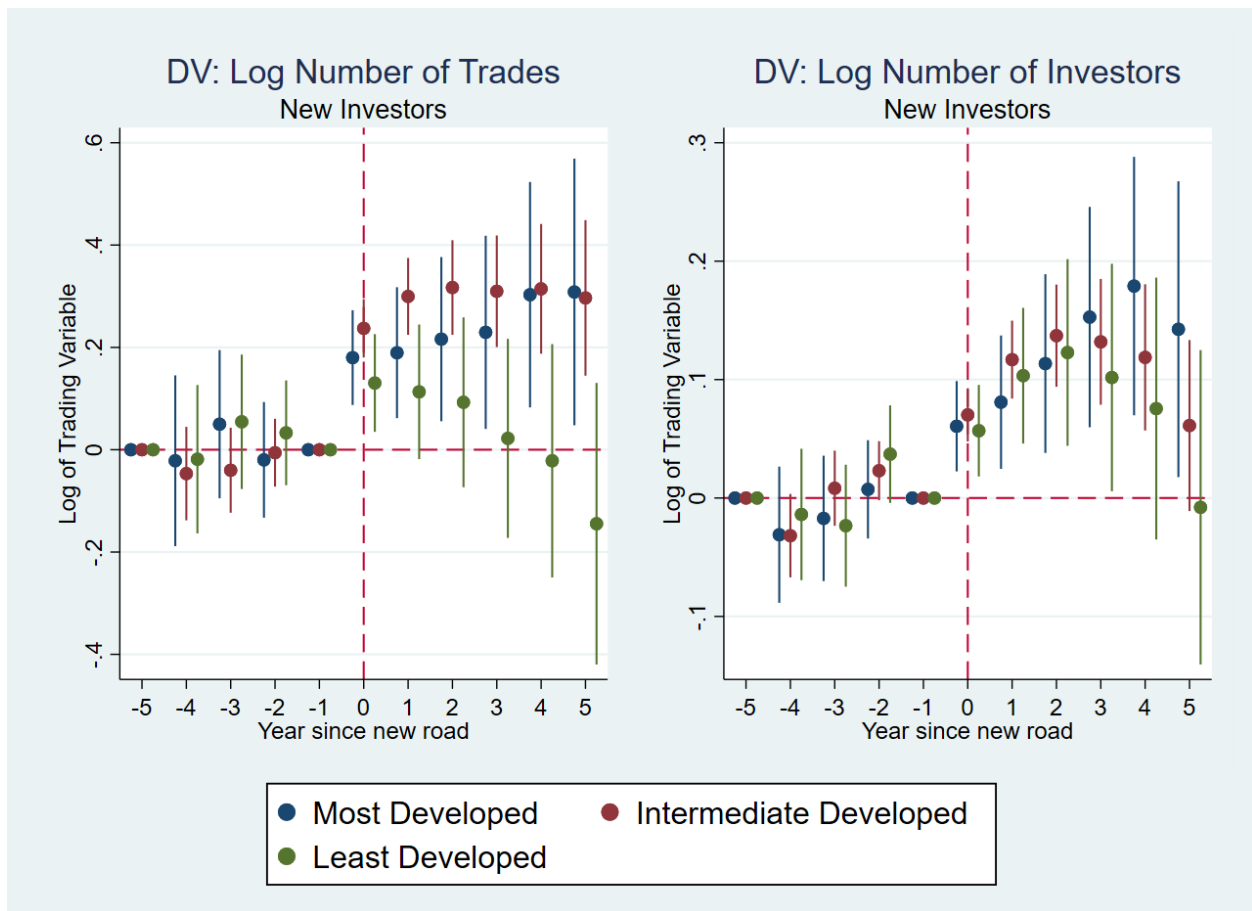


Figure 4: Time Trends of Road Impacts on Stock Tradings: By Regional Economic Development



Development Measured by Consumption Per Capita

Figure 5: Monthly Average of Stock Tradings

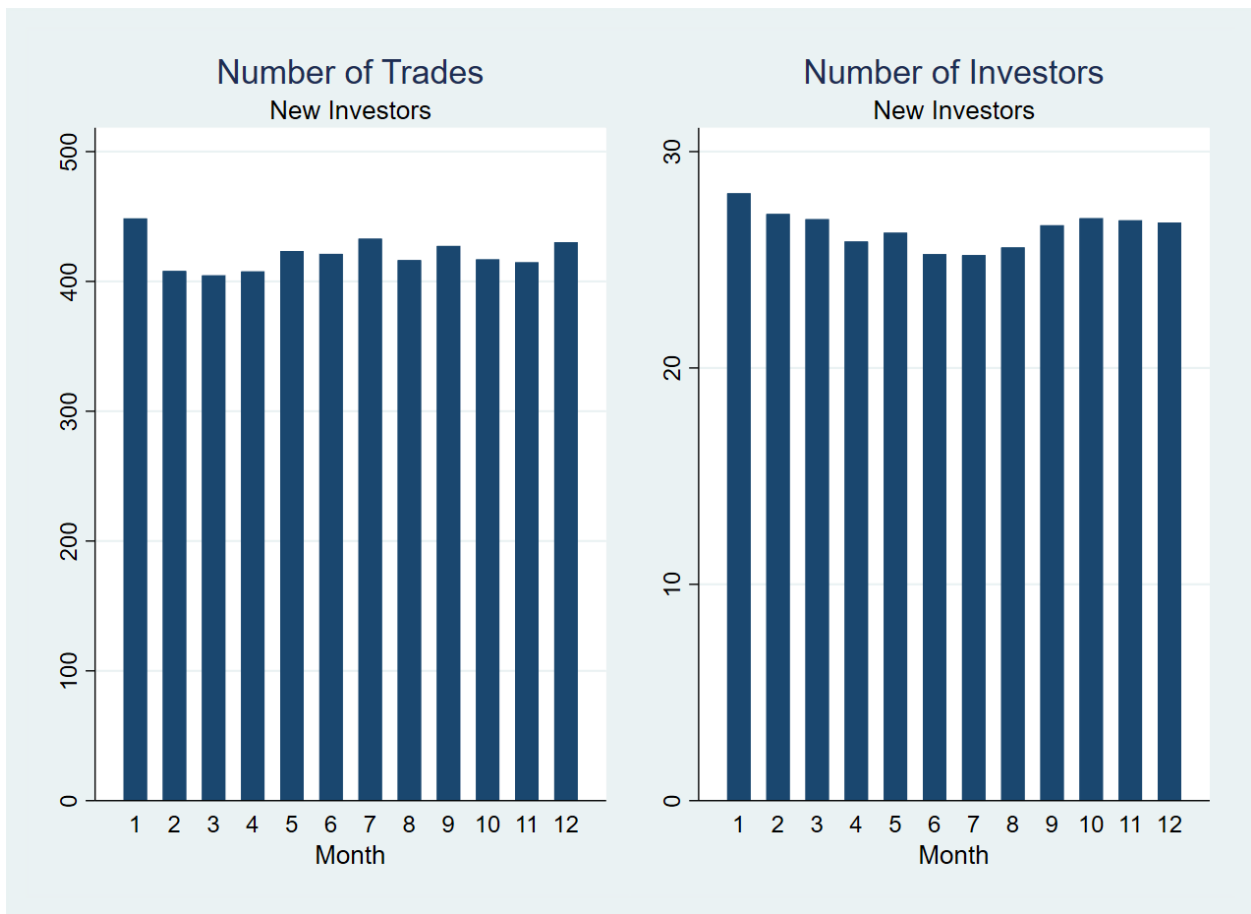


Table 1: **Summary Statistics**

This table reports the summary statistics for the key variables in our analysis. All variable definitions are in the Variable Appendix.

| | N | Mean | S.D. | Min | P25 | P50 | P75 | Max |
|--|----------|-------------|-------------|------------|------------|------------|------------|------------|
| <i>Pincode-month descriptors</i> | | | | | | | | |
| Number of Trades | 491682 | 757.087 | 1898.379 | 1 | 26 | 116 | 469 | 16669 |
| Number of Investors | 491688 | 46.462 | 114.590 | 1 | 3 | 8 | 29 | 1032 |
| Number of Tickers | 491700 | 98.177 | 131.787 | 1 | 14 | 45 | 123 | 714 |
| Share of New Investors | 491682 | 0.631 | 0.316 | 0 | 0.385 | 0.667 | 0.955 | 1 |
| Share of Experienced Investors | 491682 | 0.369 | 0.316 | 0 | 0.045 | 0.333 | 0.615 | 1 |
| Share of Young Investors | 491682 | 0.246 | 0.243 | 0 | 0.071 | .2 | 0.333 | 1 |
| Share of Middle-Aged Investors | 491682 | 0.533 | 0.266 | 0 | 0.402 | 0.532 | 0.667 | 1 |
| Share of Mature Investors | 491682 | 0.221 | 0.221 | 0 | 0 | .2 | 0.333 | 1 |
| Share of Male Investors | 491682 | 0.912 | 0.135 | 0 | 0.858 | 0.957 | 1 | 1 |
| Share of Female Investors | 491682 | 0.031 | 0.078 | 0 | 0 | 0 | 0.038 | 1 |
| Connect | 491682 | 0.667 | 0.471 | 0 | 0 | 1 | 1 | 1 |
| Rainfall Shock | 491682 | 0.028 | 0.499 | -1 | 0 | 0 | 0 | 1 |
| <i>Pincode descriptors</i> | | | | | | | | |
| Distance to city with population \geq 100K | 4154 | 45.717 | 30.392 | 0.089 | 22.970 | 39.190 | 62.087 | 275.879 |
| Distance to city with population \geq 1M | 4154 | 140.493 | 129.523 | 0.672 | 66.658 | 109.403 | 161.860 | 1025.957 |
| New Branch Dummy | 4154 | 0.432 | 0.495 | 0 | 0 | 0 | 1 | 1 |
| Number of New Branches | 4154 | 1.119 | 2.106 | 0 | 0 | 0 | 1 | 30 |
| Rural | 4154 | 0.793 | 0.405 | 0 | 1 | 1 | 1 | 1 |
| Consumption Per Capita | 4154 | 16478.11 | 5267.186 | 0 | 13506.41 | 15539.7 | 18765.04 | 66378.92 |

Table 2: **Roads and Stock Market Participation: New vs. Experienced Investors**

This table reports estimates from the following regression:

$$\text{Log}(Y_{i,t}) = \beta \cdot \text{Connect}_{i,t} + \xi_i + \kappa_t + \varepsilon_{i,t}$$

where Y are the different measures of stock market participation in each pincode i in year-month t : *Number of Trades* and *Number of Investors*. $\text{Connect}_{i,t}$ is an indicator variable which equals 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. Cols. 1 and 2 report results for the full sample, cols. 3 and 4 report results for new investors and cols. 5 and 6 report results for experienced investors. New Investors are defined as investors whose trading account opening date is ≤ 3 years old and Experienced Investors are those whose trading account opening date is >3 years. All regressions are estimated using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***) (**); (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

| | Number of Trades | Number of Investors | Number of Trades | Number of Investors | Number of Trades | Number of Investors |
|---------------|---------------------|------------------------|---------------------|------------------------|-----------------------|------------------------|
| | All Investors | | New Investors | | Experienced Investors | |
| Connect | 0.062*** (0.016) | 0.038*** (0.008) | 0.079*** (0.021) | 0.068*** (0.011) | 0.041* (0.022) | -0.025** (0.010) |
| Pincode FE | Y | Y | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y | Y | Y |
| N | 491682 | 491688 | 491682 | 491688 | 491682 | 491688 |
| Adj. R-sq | 0.819 | 0.935 | 0.725 | 0.872 | 0.797 | 0.894 |

Table 3: **Investor Heterogeneity by Gender and Age**

This table reports estimates from the following regression:

$$\text{Log}(Y_{i,t}) = \beta \cdot \text{Connect}_{i,t} + \xi_i + \kappa_t + \varepsilon_{i,t}$$

where Y are different measures of stock market participation defined in each pincode i in year-month t : *Number of Trades* and *Number of Investors*. $\text{Connect}_{i,t}$ is an indicator variable which equals 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. All estimates are for sample of New Investors, defined as investors whose trading account opening date is ≤ 3 years old. Panel A reports results for male and female investors, panel B reports results for young (18-30 years), mid-age (30-55 years) and mature investors (55+ years). All regressions are estimated using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Panel A: Heterogeneity by gender

| | 1 | 2 | 3 | 4 |
|---------------|----------------------|---------------------|------------------------|---------------------|
| | Number of Trades | Number of Investors | Number of Trades | Number of Investors |
| | Male Investors (New) | | Female Investors (New) | |
| Connect | 0.084*** (0.022) | 0.066*** (0.011) | 0.075*** (0.021) | 0.029*** (0.009) |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| N | 491682 | 491688 | 491682 | 491688 |
| Adj. R-sq | 0.714 | 0.864 | 0.614 | 0.703 |

Table 3: Investor Heterogeneity by Gender and Age (Continued...)

Panel B: Heterogeneity by age-group

| | 1 | 2 | 4 | 5 | 7 | 8 |
|---------------|-----------------------|------------------------|-------------------------|------------------------|------------------------|------------------------|
| | Number of Trades | Number of Investors | Number of Trades | Number of Investors | Number of Trades | Number of Investors |
| | Young Investors (New) | | Mid-Age Investors (New) | | Mature Investors (New) | |
| Connect | 0.086*** (0.023) | 0.046*** (0.010) | 0.083*** (0.024) | 0.062*** (0.012) | 0.161*** (0.025) | 0.088*** (0.012) |
| Pincode FE | Y | Y | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y | Y | Y |
| N | 491682 | 491688 | 491682 | 491688 | 491682 | 491688 |
| Adj. R-sq | 0.655 | 0.807 | 0.706 | 0.844 | 0.707 | 0.808 |

Table 4: **Roads and Stock Market Participation: Local Economic Development**

This table estimates the following regression:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{Rural}_i + \beta_1 \cdot \text{Connect}_{i,t} \times \text{Intermediate development}_i + \beta_2 \cdot \text{Connect}_{i,t} \times \text{Least developed}_i + \xi_i + \kappa_t + \varepsilon_{i,t}$$

where Y are different measures of stock market participation defined in each pincode i in year-month t : *Number of Trades* and *Number of Investors*. All estimates are for sample of New Investors, defined as investors whose trading account opening date is ≤ 3 years old. $\text{Connect}_{i,t}$ is an indicator variable which equals 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. In cols. 1 and 3, we use Rural_i as a measure of development where Rural_i is an indicator variable which equals to 1 if the pincode is in a rural area (as identified by the post office) and 0 otherwise. In cols. 2 and 4, we classify pincodes into *Developed(top50%)*; *IntermediateDevelopment(10 – 50%)* and *Least developed(bottom10%)* based on the values of *Consumption per Capita*. All regressions are estimated using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***) , (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

| | 1 | 2 | 3 | 4 |
|------------------------------------|-------------------------------------|---------------------|--|---------------------|
| | Number of Trades (New Investors) | | Number of Investors (New Investors) | |
| Connect | -0.416*** (0.039) | 0.022 (0.028) | -0.195*** (0.022) | 0.028* (0.015) |
| Connect X Rural | 0.623*** (0.042) | | 0.331*** (0.024) | |
| Connect X Intermediate Development | | 0.113*** (0.039) | | 0.084*** (0.020) |
| Connect X Least Development | | 0.097 (0.065) | | 0.044 (0.036) |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| N | 491682 | 491682 | 491688 | 491688 |
| Adj. R-sq | 0.728 | 0.726 | 0.874 | 0.872 |

Table 5: **Information Channel**

This table reports results from the following regression:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{Distance}_i + \xi_i + \kappa_t + \varepsilon_{i,t}$$

In Panel A, Y are different measures of stock market participation defined in each pincode i in year-month t : *Number of Trades* and *Number of Investors*. All estimates are for sample of New Investors, defined as investors whose trading account opening date is ≤ 3 years old. *Distance* is the distance between pincode i and the nearest city. In Panel B, in col. 1 Y is *Number of Tickers* traded by new investors in each pincode i in year-month t , and in cols. 2-5 Y is the *Number of Trades* in year-month t on companies that are located at the following distances from pincode i : less than 50km, 50-100kms, 100-500km, and over 500km away. $\text{Connect}_{i,t}$ is an indicator variable which equals 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. All regressions are estimated using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

| <i>Panel A: Distance from nearest city</i> | | | | |
|--|-------------------------------------|---------------------|--|---------------------|
| | 1 | 2 | 3 | 4 |
| Trading Variable | Number of Trades (New Investors) | | Number of Investors (New Investors) | |
| City Type | Tier 1 | Metro | Tier 1 | Metro |
| Connect | 0.026 (0.034) | -0.005 (0.029) | 0.060*** (0.018) | 0.021 (0.015) |
| Connect X Distance | 0.012* (0.006) | 0.006*** (0.002) | 0.002 (0.003) | 0.003*** (0.001) |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| N | 491682 | 491682 | 491688 | 491688 |
| Adj. R-sq | 0.726 | 0.726 | 0.872 | 0.873 |

Table 5: Information Channel (Continued...)

Panel B: Portfolio Diversification

| | 1 | 2 | 3 | 4 | 5 |
|---------------|--------------------------|---------------------------------------|---------------------|---------------------|---------------------|
| | Number of Unique Tickers | Number of Trades on Distant Companies | | | |
| | | < 50 Kms | 50-100 Kms | 100-500 Kms | > 500 Kms |
| Connect | 0.047*** (0.016) | 0.021*** (0.007) | 0.056*** (0.007) | 0.147*** (0.016) | 0.074*** (0.021) |
| Pincode FE | Y | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y | Y |
| N | 491700 | 491682 | 491682 | 491682 | 491682 |
| Adj. R-sq | 0.710 | 0.827 | 0.794 | 0.768 | 0.727 |

Table 6: **Financial Inclusion Channel**

This table reports estimates from the following regression:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{NewBranchDummy}_i(\text{or Number of New Branches}_i) + \xi_i + \kappa_t + \varepsilon_{i,t}$$

where Y are different measures of stock market participation defined in each pincode i in year-month t : *Number of Trades* and *Number of Investors*. All estimates are presented for sample of New Investors, defined as investors whose trading account opening date is ≤ 3 years old. $\text{Connect}_{i,t}$ is an indicator variable which equals 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. *New Branch dummy* is an indicator variable that takes the value 1 when a bank branch is opened within a 3-year window after the PMGSY road completion in pincode i and 0 otherwise. *Number of New Branches* is the total number of bank branches opened within a 3-year window after the PMGSY road completion in pincode i . All regressions are estimated using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***) , (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Panel A: All Banks

| | 1 | 2 | 3 | 4 |
|----------------------------------|-------------------------------------|---------------------|--|---------------------|
| | Number of Trades (New Investors) | | Number of Investors (New Investors) | |
| Connect | 0.003 (0.028) | 0.061*** (0.023) | 0.003 (0.014) | 0.040*** (0.012) |
| Connect X New Branch Dummy | 0.156*** (0.036) | | 0.134*** (0.019) | |
| Connect X Number of New Branches | 0.014** (0.007) | | 0.022*** (0.004) | |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| N | 491682 | 491682 | 491688 | 491688 |
| Adj. R-sq | 0.726 | 0.726 | 0.873 | 0.873 |

Table 6: **Financial Inclusion Channel (Continued...)**

Panel B: State-owned Banks vs Private Banks

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|----------------------------------|---|---------------------|--|---------------------|---|---------------------|--|---------------------|
| | Number of Trades (New Investors) | | Number of Investors (New Investors) | | Number of Trades (New Investors) | | Number of Investors (New Investors) | |
| Reference Group | Pincodes with either no branch opening or branch openings of private banks | | | | Pincodes with branch openings of private banks | | | |
| Connect | -0.002 (0.027) | 0.045* (0.023) | 0.001 (0.014) | 0.035*** (0.012) | -0.110 (0.082) | 0.099*** (0.036) | -0.042 (0.049) | 0.086*** (0.020) |
| Connect X New Branch Dummy | 0.184*** (0.036) | | 0.151*** (0.019) | | 0.264*** (0.085) | | 0.181*** (0.051) | |
| Connect X Number of New Branches | | 0.034*** (0.009) | | 0.033*** (0.005) | | 0.015 (0.009) | | 0.018*** (0.006) |
| Pincode FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y | Y | Y | Y | Y |
| N | 491682 | 491682 | 491688 | 491688 | 220191 | 220191 | 220138 | 220138 |
| Adj. R-sq | 0.726 | 0.726 | 0.873 | 0.873 | 0.781 | 0.781 | 0.902 | 0.902 |

Table 7: **Household Consumption in pincodes connected by PMGSY Roads**

This table reports estimates from the following regression:

$$Y_{h,t} = \alpha \cdot Connect_{d,t}^{CPHS} + \beta \cdot HighIncome_{h,t} + \gamma \cdot Connect_{d,t}^{CPHS} \times HighIncome_{h,t} + \eta_h + \kappa_t + \varepsilon_{h,t}$$

In panel A, Y is either $\text{Log}(\text{Consumption})$ or $\text{Log}(\text{Income})$ for each household h in year-month t . $Connect_{d,t}^{CPHS}$ is an indicator variable which equals 1 if a district, d , received a new PMGSY road between 2014 and 2015 and had not received any road under PMGSY during the previous 5 years. It takes the value 0 if the district d received no new roads under PMGSY in 2014 and 2015. $High\ Income_{h,t}$ is an indicator variable that takes the value 1 if household i 's income is above the following cutoffs and 0 otherwise: 50th, 75th, and 90th percentile of household income in that month. Standard errors clustered by household are reported in parentheses. All regressions are estimated using household and year-month fixed effects. All variables are defined in the Variable Appendix. (***) , (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Panel A: Household Expenditure & Income

| | 1 | 2 |
|------------------|----------------------|---------------------|
| | Log(Consumption) | Log(Income) |
| $Connect^{CPHS}$ | -0.051*** (0.051) | 0.115*** (0.017) |
| Household FE | Y | Y |
| Month FE | Y | Y |
| N | 125376 | 125376 |
| Adj. R-sq | 0.656 | 0.358 |

Table 7: Household Consumption in pincodes connected by PMGSY Roads (Continued...)

Panel B: Household Expenditure & Income across Income Group

| | 1 | 2 | 3 | 4 | 5 | 6 |
|--|----------------------|----------------------|----------------------|---------------------|---------------------|---------------------|
| | Log(Consumption) | | | Log(Income) | | |
| Income Level | Above 50th | Above 75th | Above 90th | Above 50th | Above 75th | Above 90th |
| <i>Connect</i> ^{CPHS} | -0.029*** (0.007) | -0.047*** (0.006) | -0.054*** (0.006) | 0.093*** (0.020) | 0.096*** (0.018) | 0.095*** (0.018) |
| High Income | 0.118*** (0.008) | 0.109*** (0.011) | 0.191*** (0.018) | 0.242*** (0.023) | 0.403*** (0.025) | 0.515*** (0.032) |
| <i>Connect</i> ^{CPHS} X High Income | -0.034*** (0.007) | -0.020** (0.009) | -0.024* (0.013) | 0.054*** (0.017) | 0.038** (0.016) | 0.026 (0.018) |
| Household FE | Y | Y | Y | Y | Y | Y |
| Month FE | Y | Y | Y | Y | Y | Y |
| N | 125376 | 125376 | 125376 | 125376 | 125376 | 125376 |
| Adj. R-sq | 0.658 | 0.657 | 0.659 | 0.362 | 0.363 | 0.362 |

Table 8: **Bank Deposits in pincodes connected by PMGSY Roads**

This table reports estimates from the following regression:

$$Deposit_{b,t} = \beta \cdot Connect_{i,t} + \phi_b + \kappa_t + \varepsilon_{b,t}$$

where *Deposit* are the log values of total amount of deposit in *Current/Saving/Term* account, and total value of deposit in branch *b* in year *t*. *Connect_{b,t}* is an indicator variable which equals 1 in the year (and thereafter) when the pincode *i*, where the branch located, in is connected by a paved road under the PMGSY program and 0 otherwise. All regressions are estimated using branch and year fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

| | 1 | 2 | 3 | 4 |
|-----------|-------------------|---------------------|-------------------|----------------------|
| | Current Account | Saving Account | Term Account | Total Deposit |
| Connect | -0.035 (0.024) | -0.031** (0.014) | -0.018 (0.019) | -0.041*** (0.014) |
| Branch FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| N | 157476 | 157483 | 157479 | 157485 |
| Adj. R-sq | 0.645 | 0.834 | 0.807 | 0.849 |

Table 9: **Roads and Local Income Shocks**

This table reports estimates from the following regression:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{RainfallShock}_{i,t} + \xi_i + \kappa_t + \varepsilon_{i,t}$$

where Y are different measures of stock market participation defined in each pincode i in year-month t : *Number of Trades* and *Number of Investors*. All estimates are presented for sample of New Investors, defined as investors whose trading account opening date is ≤ 3 years old. $\text{Connect}_{i,t}$ is an indicator variable which equals 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. $\text{Rainfall Shock}_{i,t}$ takes the value 1 if rainfall is above 80th percentile for the same pincode-month over the entire sample period; -1 if rainfall is below 20th percentile for the same pincode-month over the entire sample period; and 0 otherwise. All regressions are estimated using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***) , (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

| | 1 | 2 | 3 | 4 |
|--------------------------|-------------------------------------|---------------------|--|----------------------|
| | Number of Trades (New Investors) | | Number of Investors (New Investors) | |
| Timing of rainfall | Concurrent | One month-lag | Concurrent | One month-lag |
| Connect | 0.079*** (0.021) | 0.068*** (0.021) | 0.068*** (0.011) | 0.065*** (0.011) |
| Rainfall Shock | 0.006 (0.007) | 0.001 (0.007) | 0.007** (0.003) | 0.006* (0.003) |
| Connect X Rainfall Shock | -0.010 (0.008) | -0.003 (0.008) | -0.012*** (0.004) | -0.011*** (0.004) |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| N | 491682 | 472713 | 491688 | 472718 |
| Adj. R-sq | 0.725 | 0.723 | 0.872 | 0.874 |

Table 10: **Monetary Profits & Risk Taking**

This table reports estimates from the following regression:

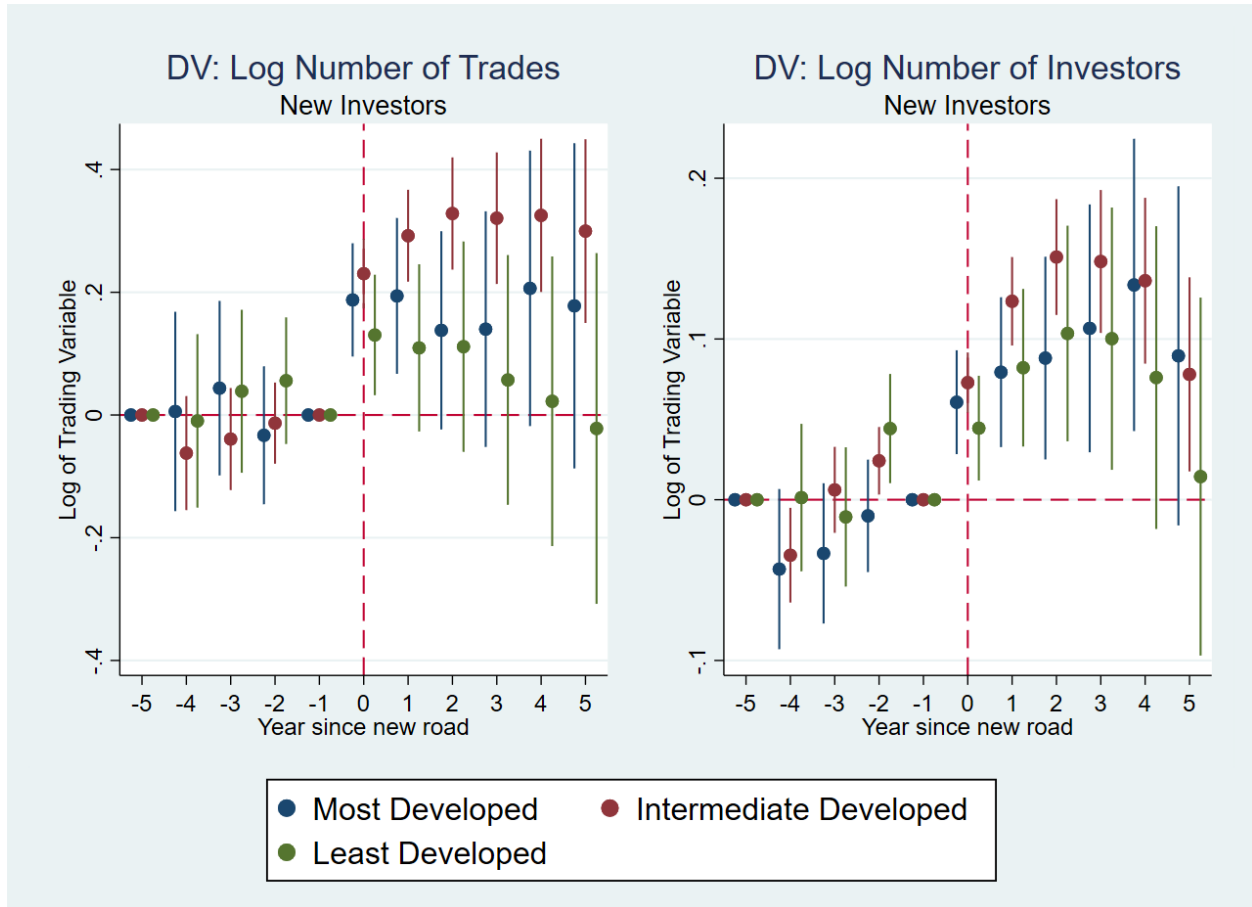
$$Y_{i,t} = \beta \cdot Connect_{i,t} + \xi_i + \kappa_t + \varepsilon_{i,t}$$

where Y are Buy-and-hold profits in Indian Rupees for buy-and-hold periods of 1/10/25/140 trading days in cols 1-4 and the monthly *Number of Trades on High Volatility Stocks* in column 5, where a stock is recognized as high volatility if its price volatility is above the sample median for all stocks in the same month. $Connect_{i,t}$ is an indicator variable which equals 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. Standard errors clustered by household are reported in parentheses. All regressions are estimated using household and year-month fixed effects. All variables are defined in the Variable Appendix. (***) , (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

| | 1 | 2 | 3 | 4 | 5 |
|----------------|---|-------------------|---------------------|-----------------------|--|
| | Average Profits (in Indian Rupees) per investor-month | | | | Number of Trades on High Volatility Stocks |
| Holding Period | 1 trading day | 10 trading days | 25 trading days | 140 trading days | |
| Connect | 10.984 (12.634) | 8.718 (39.257) | -29.136 (72.785) | -127.968 (243.729) | 0.014 (0.011) |
| Pincode FE | Y | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y | Y |
| N | 486716 | 486716 | 486716 | 486716 | 491695 |
| Adj. R-sq | 0.173 | 0.325 | 0.347 | 0.316 | 0.412 |

Appendix

Figure A1: Time Trends of Road Impacts on Stock Tradings: By Regional Economic Development



Development Measured by Poverty Rate

Table A1: **Variable Definition**

This table reports definition of each variable used in this paper.

| Variable | Definition Source | Source |
|------------------------|--|--------------------|
| Number of Trades | Total number of stock trading activities at pincode i in month t . | NSE |
| Number of Traders | Total number of stock traders activities at pincode i in month t . | NSE |
| Number of Tickers | Total number of unique tickers being traded at pincode i in month t . | NSE |
| High Volatility Stock | Stocks whose monthly price volatility is above the sample median for all stocks in the same month | NSE |
| New Investor | Investors whose overall trading experiences are less than or equal to 3 years | NSE |
| Experienced Investor | Investors who have had a trading account for more than 3 years i | NSE |
| Young Investor | Trader whose age is between 18-30 | NSE |
| Middle-Age Investor | Trade whose age is between 30-55 | NSE |
| Mature Investor | Trade whose age is beyond 55 | NSE |
| Connect | Indicator variable which equals to 1 if the pincode i is connected by a paved road at month t . | PMGSY |
| Rural | Indicator variable which equals to 1 if the post office type of that pincode is BO. | Indian Post Office |
| Developed | Indicator variable which equals to 1 if the consumption per capita(poverty rate) value of the pincode is above median value across all the pincodes in the sample. | SHRUG |
| Intermediate Developed | Indicator variable which equals to 1 if the consumption per capita(poverty rate) value of the pincode fall between the 50th and 10th percentile value across all the pincodes in the sample. | SHRUG |
| Least Developed | Indicator variable which equals to 1 if the consumption per capita(poverty rate) of the pincode is below the 10th percentile value across all the pincodes in the sample. | Census |
| New Bank | Indicator variable which equals to 1 if any new bank branches/offices open within a 3-year window after the completion of road at pincode i . | RBI |
| Number of New Banks | Total number of new bank branches/offices that open within a 3-year window after the completion of road at pincode i . | RBI |
| Distance | Distance between pincode and the nearest cities. | Census |
| Consumption | Monthly total consumption of the household. | CMIE |
| Income | Monthly total income of the household. | CMIE |
| Deposit | Year amount of deposit in bank branch. | RBI-BSR |

Table A2: **State-level distribution of investors**

This table reports the number and percentage of investors in each state who trade on the National Stock Exchange of India over the period 2004 to 2015.

| States | Number of Investors | % | States | Number of Investors | % |
|----------------|----------------------------|----------|----------------------|----------------------------|----------|
| Maharashtra | 2685160 | 19.875% | Assam | 82744 | 0.612% |
| Gujarat | 1954062 | 14.463% | Uttarakhand | 78702 | 0.583% |
| Tamil Nadu | 1046034 | 7.742% | Jammu and Kashmir | 43869 | 0.325% |
| West Bengal | 995263 | 7.367% | Himachal Pradesh | 42182 | 0.312% |
| Karnataka | 907781 | 6.719% | Goa | 38684 | 0.286% |
| Uttar Pradesh | 893399 | 6.613% | Pondicherry | 10734 | 0.079% |
| Delhi | 835927 | 6.187% | Tripura | 10383 | 0.077% |
| Rajasthan | 551151 | 4.079% | Dadra and Nagar Hav. | 5176 | 0.038% |
| Telangana | 532050 | 3.938% | Megalaya | 4729 | 0.035% |
| Kerala | 490173 | 3.628% | Chandigarh | 4574 | 0.034% |
| Andhra Pradesh | 432272 | 3.200% | Daman and Diu | 3619 | 0.027% |
| Haryana | 406657 | 3.010% | Manipur | 2740 | 0.020% |
| Madhya Pradesh | 398663 | 2.951% | Sikkim | 2674 | 0.020% |
| Punjab | 328561 | 2.432% | Nagaland | 1998 | 0.015% |
| Bihar | 228644 | 1.692% | Andaman and Nico.In. | 1526 | 0.011% |
| Jharkhand | 200192 | 1.482% | Arunachal Pradesh | 1355 | 0.010% |
| Odisha | 191229 | 1.415% | Mizoram | 604 | 0.004% |
| Chattisgarh | 96898 | 0.717% | Lakshadweep | 64 | 0.000% |
| Total | | | 13510473 | | |

Table A3: **Robustness Check: Roads and Stock Market Participation**

This table reports estimates from the following regression:

$$\text{Log}(Y_{i,t}) = \beta \cdot \text{Connect}_{i,t} + \xi_i + \kappa_t + \varepsilon_{i,t}$$

Panel A reports the results of using baseline sample adding the state-year fixed effects. Panel B reports the results of using balanced sample where we fill zeroes in pincode-month that missing on trading variables. In panel A and panel B, cols. 1 and 2 report results for all types of investors, cols. 2 and 4 report results new investors. All regressions are estimated based on using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (**), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Panel A: Adding State-Year FE to baseline setting

| | 1 | 2 | 3 | 4 |
|-------------------|---------------------|---------------------------|---------------------|---------------------------|
| | Number of Trades | Number of Investors | Number of Trades | Number of Investors |
| Type of Investors | All Investor | | New Investor | |
| Connect | 0.035** (0.016) | 0.014* (0.008) | 0.039* (0.021) | 0.034*** (0.011) |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| State-Year FE | Y | Y | Y | Y |
| N | 491682 | 491688 | 491682 | 491688 |
| Adj. R-sq | 0.823 | 0.939 | 0.734 | 0.880 |

Table A3: Robustness Check: Roads and Stock Market Participation (Continued...)

Panel B: Baseline setting on balanced panel

| | 1 | 2 | 3 | 4 |
|-------------------|---------------------|---------------------------|---------------------|---------------------------|
| | Number of Trades | Number of Investors | Number of Trades | Number of Investors |
| Type of Investors | All Investor | | New Investor | |
| Connect | 0.795*** (0.023) | 0.378*** (0.011) | 0.631*** (0.023) | 0.308*** (0.012) |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| N | 598320 | 598320 | 598320 | 598320 |
| Adj. R-sq | 0.794 | 0.875 | 0.727 | 0.825 |

Table A4: **Placebo Test: Roads and Stock Market Participation**

This table reports the placebo test of the baseline model

Panel A: Randomization for Entire Sample

| | Number of Trades | Number of Traders | Number of Trades | Number of Traders | Number of Trades | Number of Traders |
|---------------|-------------------------|-------------------------|------------------------|-------------------------|-------------------------|-------------------------|
| | All Investor | | New Investor | | Experienced Investor | |
| Connect | 0.000102 (0.0027857) | -0.000004 (0.001339) | 0.000296 (0.003719) | 0.000029 (0.001549) | -0.000043 (0.003441) | 0.000019 (0.001518) |
| Pincode FE | Y | Y | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y | Y | Y |

Table A4: Placebo Test: Roads and Stock Market Participation (Continued...)

Panel B: Randomization within Each Month

| | Number of Trades | Number of Traders | Number of Trades | Number of Traders | Number of Trades | Number of Traders |
|---------------|------------------------|-------------------------|------------------------|-------------------------|------------------------|-------------------------|
| | All Investor | | New Investor | | Experienced Investor | |
| Connect | 0.000042 (0.002727) | -0.000066 (0.001344) | 0.000221 (0.003694) | 0.000012 (0.001615) | 0.000032 (0.003306) | 0.000062 (0.001405) |
| Pincode FE | Y | Y | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y | Y | Y |

Table A5: **Roads and Stock Market Participation: Local Economic Development**

This table estimates the following regression:

$$\text{Log}(Y_{i,t}) = \alpha \cdot \text{Connect}_{i,t} + \beta \cdot \text{Connect}_{i,t} \times \text{Rural}_i + \beta_1 \cdot \text{Connect}_{i,t} \times \text{Intermediate development}_i + \beta_2 \cdot \text{Connect}_{i,t} \times \text{Least developed}_i + \xi_i + \kappa_t + \varepsilon_{i,t}$$

where Y are different measures of stock market participation defined in each pincode i in year-month t : *Number of Trades* and *Number of Investors*. All estimates are presented for sample of New Investors, defined as investors whose trading account opening date is ≤ 3 years old. $\text{Connect}_{i,t}$ is an indicator variable which equals to 1 in the year-month (and thereafter) when a pincode is connected by a paved road under the PMGSY program and 0 otherwise. In cols. 1 and 3, we use Rural_i as a measure of development where Rural_i is an indicator variable which equals to 1 if the pincode ranked as the tier-3 pincode and 0 otherwise. In cols. 2 and 4, we classify pincode into *Developed(top50%)*; *IntermediateDevelopment(10 – 50%)* and *Least developed(bottom10%)* based on the values of *Poverty Rate*. All regressions are estimated using pincode and year-month fixed effects. Standard errors clustered by pincode are reported in parentheses. All variables are defined in the Variable Appendix. (***), (**), (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

| | 1 | 2 | 3 | 4 |
|------------------------------------|-------------------------------------|---------------------|--|---------------------|
| | Number of Trades (New Investors) | | Number of Investors (New Investors) | |
| Connect | -0.423*** (0.051) | 0.011 (0.028) | -0.195*** (0.029) | 0.026* (0.015) |
| Connect X Rural | 0.559*** (0.053) | | 0.293*** (0.030) | |
| Connect X Intermediate Development | | 0.135*** (0.039) | | 0.091*** (0.020) |
| Connect X Least Development | | 0.119* (0.064) | | 0.043 (0.036) |
| Pincode FE | Y | Y | Y | Y |
| Year-Month FE | Y | Y | Y | Y |
| N | 491682 | 491682 | 491688 | 491688 |
| Adj. R-sq | 0.727 | 0.726 | 0.873 | 0.873 |