Open Payment Systems and Retail Market Access: Evidence from India's UPI

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We examine how digital payment infrastructure affects retail investor behavior using India's Unified Payments Interface (UPI) across banks. Using the universe of retail trading data from the National Stock Exchange covering 19.8 million investors (2015-2020), we find that regions with greater exposure to early UPI-adopting banks experience significant increases in trading activity and investor participation. A one standard deviation increase in UPI exposure leads to a 6.1% increase in monthly transactions and an 8.6% rise in active investors relative to pre-treatment means. We establish causality through multiple identification strategies: comparing trading across accounts of the same investor, exploiting exogenous variation in UPI access from a bank merger, and contrasting UPI's effects with a bank-specific digital platform. We identify three key mechanisms through which these effects operate: reduced transaction frictions enabling faster response to market events, lower barriers to entry for small investors, and network externalities from the broader digital ecosystem. While UPI adoption increases market participation, it also leads to concerning trading patterns among small investors, including reduced diversification and negative excess returns over longer horizons. These findings demonstrate how payment infrastructure can democratize market access while potentially introducing new risks for retail investors.

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1. Introduction

Efficient and accessible payment systems that facilitate seamless fund transfers between individuals, businesses, and governments are fundamental to the functioning of financial markets, financial stability, and overall economic growth.[1] However, traditional payment systems have significant limitations that restrict financial market participation, including processing delays, restricted operating hours, and substantial transaction costs. These frictions disproportionately affect small investors, limiting their ability to quickly access capital markets and react to investment opportunities.

To address these inefficiencies, many countries have introduced real-time payment systems aimed at increasing speed, reducing costs, and expanding accessibility.[2] These innovations are particularly transformative in developing economies, where high transaction costs and infrastructure constraints have historically excluded large populations from formal financial services (e.g., Demirguc-Kunt et al. (2018)). While recent research has explored how instant payment systems improve financial inclusion and banking access - such as expanding expand credit access (e.g., Gonzalez et al. (2024), Alok et al. (2024)) and intensifying deposit competition (e.g., Sarkisyan (2023)) - little is known about their impact on capital market participation.

This paper fills that gap by examining how India's Unified Payments Interface (UPI) system affects retail trading activity and market participation. UPI offers a uniquely powerful setting to study this question because it removes key barriers to investing in financial markets. Unlike closed-loop payment systems such as China's Alipay or Kenya's M-Pesa), UPI's open, interoperable protocol architecture seamlessly connects banks, fintech applications, and trading platforms. The system addresses multiple frictions in traditional payment systems by eliminating settlement delays through instant transfers, offering zero-cost transactions compared to conventional bank transfer fees, and providing real-time visibility of account balances and settlements. These features particularly benefit retail investors who are more sensitive to transaction costs and timing constraints. Furthermore, UPI's integration with market infrastructure through specialized payment

[1] See BIS (2020), IMF (2019), and Bank (2018).

[2] Notable examples include India's Unified Payments Interface (UPI), Brazil's Pix, the U.S. FedNow, the EUs Target Intant Payment Systems (TIPS), and the UKs Faster Payments System. See the World Bank 2021 Report on Fast Payments Systems for a comprehensive listing of fast payment systems around the world. Available at https://fastpayments.worldbank.org/

rails for activities like IPO applications makes it an integral component of the trading ecosystem rather than just a payment channel. The system's widespread adoption – processing over 13 billion transactions worth 20 trillion rupees monthly by June 2024 – provides sufficient scale to study its impact on market participation.[3]

Our study leverages the differential adoption of UPI across Indian banks between 2015-2020, using the universe of retail trading transactions on the National Stock Exchange (NSE) covering over 19 million retail investors. This setting offers three key advantages: First, bank-level variation in UPI adoption timing helps isolate its effects from other country-wide policy changes. Second, India's rapid digitization during this period, coupled with its booming stock market, provides an ideal laboratory to examine how payment innovation shapes market participation. Third, our granular data allows us to track individual trading patterns and identify specific mechanisms through which payment infrastructure affects market access.

We present several novel findings. First, we find that UPI adoption leads to increased stock market activity, both in terms of number of transactions and number of investors. Pincodes with greater UPI exposure have a greater number of retail trades as well as a higher number of retail investors following the adoption of UPI in 2016. The number of transactions in a month increases by 68 transactions in with one standard deviation increase of UPI Exposure in pincodes, an increase of 6.1% relative to the pre-treatment mean. The number of investors participating in the stock market in a pincode-month also increases by 7, following UPI adoption in high UPI exposure pincodes relative to low UPI exposure pincodes. Second, we identify three specific (and complementary) mechanisms - reduction in transaction frictions for active investors responding to market events, lowering of entry barriers for small investors, and leveraging existing digital payment networks - through which UPI adoption influences stock market participation. Finally, we show that the easier access to trading via open payment infrastructure comes with unintended consequences, including riskier trading and less diversification by small investors.

To investigate the relationship between UPI adoption and stock market activity, we leverage several unique datasets. For our baseline results, we use comprehensive data on stock trading

[3]See statistics from the National Payments Corporation of India (NPCI). Available at https://www.npci.org.in/what-we-do/upi/product-statistics. Last accessed July 30, 2024

activity on the National Stock Exchange (NSE) of India by over 19 million individuals/households from 2015 to 2020. The data is daily aggregate data by investor-stock-buy/sell position and includes information on the exact pincode location of each trader (or investor), trader demographics such as age and gender, and the specific stocks traded. We supplement the NSE data with two other trading datasets - first, we obtain trading data from one of the leading brokerage firms in India that provides richer detail on individual investors including education, income, occupation, and credit score, allowing us to explore heterogeneity in investor types; second, we use high-frequency time-stamped transaction level (tick by tick) data from the Bombay Stock Exchange (BSE)[4] for a 12-hour window around flash crashes in September 11, 2019, and March 12, 2020, allowing us to examine the role of UPI in enabling investors to respond faster to sudden market movements. In addition, we use bank branch-level deposit data from the Reserve Bank of India (RBI) to construct the pincode-level UPI exposure measure. Following Alok et al. (2024), we define *UPI Exposure* for a pincode as the share of total deposits of *early* adopter banks over the total deposits of all banks,[5] the idea being that due to strong network externalities,[6] pincodes where early UPI adopter banks are dominant players are more likely to see the highest growth in stock market participation.

Our identification exploits two key sources of variation in UPI adoption: the timing of banks joining the platform and their market presence across different pincodes. We define high UPI-exposure pincodes as those where early-adopter banks have a dominant market share. This dual variation in adoption timing and geographic presence helps address potential confounding effects from broader policy changes or market conditions at the country-level. Since banks made UPI adoption decisions at the institutional level rather than regional level, our approach also mitigates concerns about local factors driving both UPI adoption and trading outcomes. Using a difference-in-differences framework, we compare trading activity between high and low UPI-exposure pincodes before and after UPI implementation. Supporting our identification strategy, a pre-trend analysis shows no significant differences in stock market activity in the pre-treatment period between high

[4]The BSE and NSE are the two key exchanges in India. While the BSE is the oldest and first stock exchange in Asia, the NSE is younger but also the largest stock exchange, in terms of trading volume, in the country.

[5]Dubey and Purnanandam (2023) also use a similar definition of UPI Exposure but their definition is at the district level. We have more granular data on bank lending at the pincode level.

[6]A growing fintech literature (e.g. Crouzet et al. (2023), Higgins (2022), Fafchamps et al. (2022)) has established the importance of adoption externalities where early adoption of the technology by a core number of users can have persistent effects. Mishra et al. (2022) also document the stickiness in technological adoption by Indian public sector banks.

and low UPI exposure pincodes.

As robustness, we construct a shift-share Bartik instrument using UPI transaction volumes and combine it with geographic variations in early UPI adoption (measured as of September 2017) and subsequent national-level adoption trends. This identification strategy leverages pincode-level UPI changes that are driven by nationwide factors affecting UPI adoption.

In all the regressions, we control for pincode fixed effects and district-time fixed effects. Thus, our results are not driven by high UPI exposure pincodes being wealthier or more developed than low UPI exposure pincodes, which may independently influence trading activity in these pincodes. The district-time fixed effects also control for any time-varying economic policies which are usually implemented at the district level (rather than pincode level). In addition, one concern could be that the varying local effects of demonetization is driving our results rather than UPI adoption. Chodorow-Reich et al. (2020) show that districts experiencing more severe demonetization had faster adoption of alternative payment technologies which then might lead to greater stock market investment. However, our UPI Exposure measure is not correlated with the distance to currency chests, which have been shown to be a key determinant of the local severity of demonetization effects in Chodorow-Reich et al. (2020). Thus, our exposure instrument captures effects orthogonal to the demonetization event.

To strengthen our causal interpretation, we address three main identification concerns. First, we address potential omitted variables at the pincode-month level. We focus on investors with multiple brokerage accounts and compare their trading activity between brokerage accounts linked to early adopter banks versus late adopter banks, after UPI adoption. Using data at the investor-broker-year-month level data, with investor-time, broker, and district-time fixed effects, we find higher trading activity in accounts linked to early-adopter banks. This within-investor analysis suggests that the increase in stock market activity in pincodes with high exposure to UPI is not driven by local economic conditions varying at the pincode month levels.

Next, we address selection concerns regarding early-adopter banks. These banks might be technologically advanced overall, potentially introducing other innovations that confound the effect of UPI adoption. To explore this, we conduct two types of tests. First, we exploit an exogenous

source of UPI access through a bank merger. Specifically, we focus on the merger between Canara Bank (an early UPI adopter) and Syndicate Bank (late-adopter) on August 11, 2019 [7] and restrict the sample to investors with trading accounts in these banks prior to the merger. We observe increased trading activity, both number of transactions and number of securities, in accounts that gained UPI access through this merger within four weeks post merger.

Second, we compare UPI's impact against YONO, a closed banking application launched by the State Bank of India (SBI) in 2017. We conjecture that since the open payment framework under UPI offers more flexibility due to its interoperability across banks than YONO which primarily serves customers with SBI accounts, we should see a greater impact from UPI exposure than YONO exposure. To test this, we first restrict the sample to only trading activity in accounts linked to SBI. Next, we construct a measure of YONO exosure at the pincode level, similar to the UPI exposure measure, and run a horse race between the two measures. When we include both UPI exposure and YONO exposure in the same regression, we find significant effects from UPI exposure. The YONO exposure measure, while significant, is weaker than the UPI exposure measure in influencing trading behavior. This result suggests that the open banking framework plays a unique role in influencing investors to participate in the stock market. It also helps allay the concern that our results might be driven by bank specific fundamentals.

Finally, we address concerns about customer selection at early adopter banks. We find no significant pre-treatment differences between high and low UPI exposure pincodes across various demographic characteristics. This includes age and gender from NSE data, as well as income, occupation, credit score, and education from broader demographic data available in the brokerage dataset.

Overall, our findings reveal increased trading activity, both in the number of transactions and number of investors, in pincodes with greater exposure to early UPI-adopting banks. To understand the underlying drivers, we investigate three distinct but potentially complementary mechanisms:

First, UPI's impact likely stems from reducing transaction costs through instant fund transfers.

[7] While there have been other bank mergers over our sample period, this is the only merger where the banks have independent brokerage houses. The merger resulted in the fourth largest public sector bank in the country. See https://www.businesstoday.in/industry/banks/story/canara-bank-syndicate-bank-merge-become-4th-largest-public-sector-bank-223504-2019-08-30

Conventional fund transfer methods like Real-time Gross settlements (RTGS) and National Electronic Funds Transfer (NEFT) operate in batch processing mode during limited banking hours, requiring users to input detailed account information for each transaction and impose significant transaction costs. In contrast, UPI enables instant, round-the-clock fund transfers using just a phone number or user ID, with zero transaction costs. A key advantage of UPI is that it facilitates both instant fund transfers and receipts, allowing investors to monitor all money movements in real-time through the UPI app. This visibility and immediacy in both sending and receiving funds provides investors with greater confidence and control over their trading activities, particularly during time-sensitive market situations. This fundamental transformation in payment convenience, cost, and transparency particularly benefits retail investors who might otherwise miss market opportunities due to transfer delays or be deterred by transaction fees.

To empirically validate this mechanism, we analyze high-frequency trading data from the Bombay Stock Exchange during two significant flash crashes (September 11, 2019, and March 12, 2020). Examining 12-hour windows before and after these crashes, with granular investor and hour fixed effects, we find substantially higher trading activity in high UPI exposure pincodes. The immediacy of response during these market events suggests that UPI's instant transfer capability enables investors to quickly capitalize on market movements. This real-time trading response would be considerably more difficult under traditional banking systems where fund transfers might take hours or days to process.

Second, UPI adoption could democratize investment opportunities by reducing barriers to entry. Traditional investment processes often involve cumbersome documentation and complex fund transfer procedures that can discourage small investors. UPI simplifies this through streamlined onboarding, seamless fund transfers, and reduced costs. Our empirical analysis strongly supports this democratization effect. In pincodes with high UPI exposure, we observe a significant increase in small transactions and greater participation from small investors [8] This pattern suggests that UPI's simplified infrastructure particularly benefits previously underserved investors who might have found traditional investment channels intimidating or inaccessible. The increase in small-value transactions indicates that UPI enables investors to start with modest amounts, potentially

[8]Following Lee and Radhakrishna (2000) and Malmendier and Shanthikumar (2007), we define small investors with monthly transaction values in the bottom 30 percent of transactions in terms of trading value in that month.

making stock market participation more accessible to a broader demographic.

Third, UPI's impact could operate through the enhancement of the digital financial ecosystem, particularly by leveraging and strengthening existing digital infrastructure. In areas where users regularly use digital payments for transactions, there should be lower psychological barriers and reduced technical friction in UPI adoption and usage for investment purposes. To empirically validate this mechanism, we proxy areas with differing digital service penetration by an urban-rural classification. We find significantly stronger effects in urban areas, where digital service usage is more prevalent. This suggests that the digital ecosystem mechanism acts as a multiplier, amplifying UPI's effectiveness in areas with stronger digital foundations. This mechanism helps explain why identical UPI infrastructure might have varying impacts across different locations, suggesting that the success of open banking initiatives depends not just on the technology itself, but on its integration with and leveraging of the broader digital ecosystem.

Finally, we explore the consequences of easier access. While easier access enhances market participation, it may lead to suboptimal investment behaviors such as excessive risk taking, particularly among small investors. Our analysis of trading patterns reveals that in high UPI exposure pincodes, while overall portfolio diversification increases, the returns pattern is concerning. Despite initial positive returns for small investors over 10-day periods, longer-term analysis over 140 days shows negative excess returns across all investor categories. More worryingly, small investors in high UPI exposure areas display potentially problematic trading patterns: reduced diversification, increased trading frequency, and greater preference for high-risk stocks. These findings suggest that while UPI successfully reduces market access barriers, it might inadvertently encourage excessive trading and risk-taking among less experienced investors.

Our study contributes to several interconnected streams of literature examining how technological innovation in payment systems reshape financial intermediation. First, we add to the rapidly growing research on next-generation payment systems, including fast payment systems, stablecoins, and central bank digital currencies (CBDCs). As Brunnermeier et al. (2019) and Duffie (2019) highlight, these innovations are fundamentally reshaping the financial landscape. While most studies in this area have focused on consumption and basic financial inclusion – such as Jack and Suri (2014)'s analysis of mobile money adoption in Kenya and Muralidharan et al. (2016)'s examina-

tion of biometric payment systems – our paper extends this literature by examining how payment innovation affects sophisticated financial behavior through stock market participation.

A nascent but growing body of work specifically examines how instant payment systems transform financial intermediation: Ouyang (2021) examine cashless payments (Alipay in China) and financial inclusion, Ghosh et al. (2022) study fintech lending, and Sarkisyan (2023) analyzes how Brazil's Pix system affects deposit competition. Liang et al. (2024) build on Sarkisyan (2023) by showing how instant payments amplify monetary policy transmission through increased deposit competition. In the specific context of UPI, Dubey and Purnanandam (2023) document UPI's role in broader financial inclusion in India while Alok et al. (2024) show that adoption led to an increase in credit to marginal and unserved borrowers. Our analysis differs importantly from previous work in both focus and methodology. While Dubey and Purnanandam (2023) use the UPI setting to examine impacts on household income and small business activities, our granular data covering the universe of stock market transactions allows us to analyze how open payment infrastructure affects stock market investment activity. Critically, our pincode-level exposure measure, compared to their district-level measure, helps us control for confounding local economic factors and policy changes that typically operate at the district level. Combined with the investor-level tests, our empirical methodology allows us to provide clean identification of how payment infrastructure affects market participation while controlling for concurrent economic changes.

Our work also connects to the emerging literature on open banking and its implications for market structure and consumer welfare. Recent theoretical work has examined the welfare implications of open banking frameworks: Parlour et al. (2022) analyze how payment system innovation affects bank competition and consumer welfare, while He et al. (2023) develop a framework for understanding how data sharing in open banking affects credit market efficiency. Goldstein et al. (2022) show that open banking can reduce information asymmetries but may have distributional consequences across consumer types. Babina et al. (2024) provide empirical evidence on how customer data sharing through open banking affects banking relationships and credit outcomes. While these studies focus primarily on credit markets and banking relationships, our work extends this literature by examining how open payment infrastructure affects participation in capital markets.

Finally, our study contributes to the broader literature on technological innovation and retail

investor behavior. Building on studies such as Barber and Odean (2001) who examine how online trading affects investor performance, and more recent work by Parlour et al. (2022) on FinTech and market participation, we show how reducing payment frictions through technological innovation can alter trading patterns while potentially introducing new risks.

Our findings on small investor trading patterns following UPI adoption contribute to the broader debate on whether technological innovations that reduce market frictions necessarily improve investor outcomes. While Campbell (2006) highlights how reducing participation costs can enhance household welfare through better diversification opportunities, subsequent research has revealed potential downsides of lower market frictions. Barber et al. (2022) show how reduced trading frictions can lead to excessive speculation, while Frydman and Wang (2020) document that increased trading accessibility can amplify behavioral biases. Our results extend this literature by showing that while UPI adoption increases market participation, it appears to encourage potentially problematic trading patterns among small investors, including reduced diversification and negative excess returns over longer horizons.

2. Institutional Context and Data

2.1. The Unified Payments Interface (UPI)

Instant payment systems have revolutionized financial markets worldwide, facilitating seamless and immediate transactions. Notable examples include Brazil's Pix, India's UPI, and the United States' FedNow. These systems mark a departure from traditional batch-processing methods, replacing them with real-time settlement frameworks. While systems like Pix and FedNow primarily focus on general-purpose payments, India's Unified Payments Interface (UPI) stands out for its deep integration with securities trading infrastructure.

Launched in 2016 by the National Payments Corporation of India (NPCI), UPI has achieved unprecedented scale, processing over 16 billion transactions as of December 2024.[9] Its architecture comprises three distinct layers: (1) a settlement layer operated by NPCI, (2) a bank interface layer

[9]See Payment Systems Report 2024, a bi-annual report from the Reserve Bank of India.

where Payment Service Providers (PSPs) connect to the system, and (3) a user interface layer featuring both bank-owned and third-party applications like Google Pay and PhonePe.

Unlike closed-loop payment systems (e.g. China's Alipay or WeChat; Kenya's M-Pesa; United States' Zelle) where transactions are restricted within proprietary networks, UPI operates as an open protocol that enables interoperability across banks, fintech applications, and trading platforms.

UPI's integration with securities trading infrastructure addresses three critical frictions that have historically impeded retail market participation: First, traditional payment systems like the National Electronic Funds Transfer (NEFT) imposed settlement delays of 1-2 business days, creating substantial opportunity costs for traders requiring immediate market access. UPI eliminates this bottleneck by enabling instantaneous trading account funding, allowing investors to capitalize on market opportunities in real-time. Figure A.1 in the Appendix presents an infographic highlighting the ease of transfer of funds for investing via UPI versus traditional payment methods.

Second, while regulatory requirements mandate the separation of retail banking and securities operations in India, UPI provides a compliant bridge between these segregated accounts through a three-step verification protocol. Third, UPI has transformed the initial public offering (IPO) subscription process through specialized payment rails, significantly reducing the procedural complexity that previously deterred retail participation. [10]

Thus, UPI's impact on trading extends beyond mere convenience, representing a fundamental shift in how retail investors interact with financial markets. By eliminating traditional payment barriers and reducing transaction friction, UPI has democratized market access and contributed to the growing participation of retail investors in India's securities markets.

[10]The One Time Mandate (OTM) system, introduced by SEBI in 2019, revolutionized IPO applications by integrating with UPI to create a seamless blocking mechanism for funds. Through this system, retail investors can apply for IPOs using their UPI ID, and upon authorization through UPI PIN, the specified amount is blocked in their bank account not debited until share allotment. This UPI-based mandate system significantly shortened the IPO application process, eliminated the need for physical forms, and made the process more efficient for retail investors.Figure A.2 in the Appendix shows a chart from the RBI's Payment Systems Report documenting the increasing use of UPI-enabled IPO applications.

2.1.1. UPI vs. Other Instant Payment Systems

Instant payment systems represent a fundamental shift in payment infrastructure, enabling real-time, 24/7 settlement of transactions. These systems have emerged globally with varying implementation approaches, regulatory frameworks, and adoption rates. This section contextualizes UPI's adoption by comparing it with other major global payment systems.

In the United States, payment settlement has traditionally relied on batch-processing systems with settlement times of 1-3 business days. The launch of FedNow in July 2023 introduced 24/7 instant payments, yet adoption has remained limited, particularly among major banks. By January 2024, FedNow had enrolled 400 banks, but its decentralized, voluntary implementation contrasts sharply with India's approach. Unlike the U.S., India mandated UPI integration for all banks with over 10 million customers, accelerating system-wide adoption. Additionally, whereas FedNow primarily facilitates bank-to-bank transfers, UPI operates as a holistic payment ecosystem, integrating banks, third-party apps (e.g., Google Pay, WhatsApp), and merchants through a unified framework.

In contrast, Brazil's Pix, started in 2020 shares several similarities with UPI. Both systems were developed by national payment authorities – NPCI in India and the Central Bank of Brazil for Pix – ensuring standardized implementation and broad adoption. They also employ simple, user-friendly identifiers (CPF/phone numbers for Pix, Virtual Payment Address for UPI), reducing reliance on complex banking details. Consequently, both UPI and Pix have achieved significant penetration in their respective markets.

Other prominent instant payment systems include the European Unions SEPA Instant (2017), the UK's Faster Payments Service (2008), and Singapore's PayNow (2017). While these systems effectively enable real-time transactions, they primarily focus on bank-to-bank transfers and lack UPI's expansive ecosystem integration.

UPI's distinctive contribution lies in its transformation of retail market participation mechanisms. By eliminating traditional payment frictions and establishing direct connectivity with trading infrastructure, UPI has fundamentally altered how retail investors access capital markets. This

integration represents more than a technological advancement; it constitutes a structural change in market accessibility that may have significant implications for market participation and price formation.

2.2. UPI Exposure Measure

The accessibility of UPI is contingent on bank participation in the UPI platform, with users requiring an account at a UPI-member bank to generate a virtual address and initiate transactions. Thus, an individual is able to use digital payments only if their bank participates on the UPI Platform. This allows us to use the spatial and temporal variation in adoption of UPI by member banks to construct a measure of UPI exposure at the pincode level. Specifically, following Alok et al. (2024), UPI Exposure for a pincode, p, is defined as the share of total deposits of early adopter banks over the total deposits of all banks, as of 2015, the year before UPI was introduced:

$$\text{UPI Exposure}_p = \frac{\text{Total Deposits of Early Adopter Banks}_p}{\text{Total Deposits of All Banks}_p} \tag{1}$$

Early adopter banks are those that had adopted UPI as of November 2016.[11] The deposit data by bank branch and pincode is obtained from the Basic Statistical Returns (BSR), proprietary data from the Reserve Bank of India (RBI). We first map the bank branches to pincode location and aggregate deposits to the bank-pincode level using data as of March 31st, 2016 (end of fiscal year and the latest data available before widespread UPI adoption in November 2016).

The index exploits two sources of variation. First, as noted in Dubey and Purnanandam (2023) and Alok et al. (2024), not all banks adopted UPI at the same time, and the decision to adopt UPI was made at the bank level, not at the bank branch level. Thus, there is variation in UPI adoption across pincodes based on the timing of a bank's participation on the platform, which is arguably unrelated to the unobserved heterogeneity of pincodes. While early adopter banks can potentially differ in significant ways from late adopter banks, for example because they predict greater adoption or are more technologically savvy, the pincode level variation ensures that demand and other factors

[11] The list of early adopter banks is published by the Government of India. The number of banks that were live on UPI increased from 21 in August 2016 to 362 as of April 2023. See https://www.npci.org.in/what-we-do/upi/live-members.

local to individual pincodes are not driving the decision for banks to adopt UPI. This is particularly true for India, where 95% of lending is by scheduled commercial banks and driven by only around 50 banks serving either nationally or at the state level and not concentrated in narrow pincodes or districts. Further, the pincodes are used for and defined by the Indian Postal Service, ensuring that policies that are usually targeted based on administrative units do not confound our results.

Second, the measure relies on geographic variation in bank deposits of early and late adopters. The intuition behind this index is that regions where early UPI adopter banks are dominant players are more likely to be extensive adopters of digital transactions due to strong network externalities as documented in Higgins (2022) and Crouzet et al. (2023). Thus, the fraction of depositors in early adopter banks in a pincode predict UPI usage in that pincode.

While we choose to rely on the UPI exposure index as our main measure, we also construct a Bartik instrument to supplement our analysis. Specifically, we construct the Bartik instrument using the following equation:

$$\text{UPI Bartik}_{p,t} = \text{National UPI}_t \times \frac{\text{UPI}_p}{\text{GDP}_p} \tag{2}$$

where UPI_p is total number of UPI transactions in each pincode as of September 2017 and GDP_t is the GDP level (proxied by the night light indexes) at the pincode.[12] This measure allows us to capture the time-varying Bartik instrument where the time variation is coming from the national changes in UPI, which is exogenous to local demand factors and ex-ante share of UPI across different region. The identifying assumption in the Bartik setup is that pincodes with varying exposures have similar time trends in the absence of treatment (Borusyak et al., 2021). We examine this identifying assumption more formally in Section 3. We normalize the Bartik instrument using the sample mean and standard deviation values. The normalized Bartik instrument is standardized to have a mean of zero and a standard deviation of one.

Figure 1 provides maps on the geographical distribution of the UPI exposure and UPI Bartik measure acorss different pincodes of India. From both maps, we see that pincodes in the central part of India have higher UPI exposure as indicated by the brighter colors for both measures. Table

[12] As robustness, we also use the total number of UPI transactions for January 2017 and the average across Jan-Sept 2017 and yield similar results

1 shows that the average UPI exposure in each pincode is 0.65 signifying that, on average, early adopter banks accounted for 65% of deposits in a pincode. The measure ranges from from 0 to 1 indicating the wide variance in coverage across pincodes in India. In Figure 3, we show that high-exposure pincodes exhibit higher UPI usage, validating our exposure measure.

2.3. Trading Data

We use data on the universe of individual investors' daily trading activity compiled by the National Stock Exchange of India over the period 2015 to the first quarter of 2020. We restrict our sample to individual investor accounts and trading of domestic stocks. 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. The NSE data also contains demographic details on the investors including each investors gender, age, and residential pincodes. Following the procedure in Agarwal et al. (2021), we match the pincodes in the NSE dataset to the official list of post office pincodes published by the Indian government.[13]

2.3.1. Pincode-level Measures

As our main measures of stock market participation, we construct the following two variables: *Number of Transactions*, defined as the total number of trades within a pincode during a specific year-month, and *Number of Investors*, defined as the total number of active investors within a pincode during the same period. Active investors are those with recorded trading activity in the given month. The summary statistics in Table 1 show that each pincode averages approximately 1,108 transactions per month, involving 81 active investors.

Figure 2 illustrates the time trends of the average *Number of Transaction* and *Number of Investors* over our sample period. The figure shows that between 2015 and 2020, the monthly average number of transactions increased by 55.3% from 1386 to 2153 while the monthly average number of investors participating in the stock market also increased by 83.5%.

[13] See https://data.gov.in/catalog/all-india-pincode-directory

FIGURE 2 ABOUT HERE

To examine how these trading patterns correlate with UPI adoption, we classify pincodes into High UPI exposure (median and above) and Low UPI exposure (below median) poncodes. Figure 3 plots the difference in the number of transactions and investors between High and Low UPI exposure pincodes over time. The figure shows that the gap between high- and low-exposure areas widens over time, suggesting a positive correlation between UPI adoption and increased market participation.

FIGURE 3 ABOUT HERE

To explore the heterogeneity in the effects of UPI based on investor type, we follow Lee and Radhakrishna (2000) and Malmendier and Shanthikumar (2007) and define small and large investors. Specifically, we consider an investor to be a small investor if his/her total transaction value for a particular month is in the bottom 30 percent of transactions in terms of trading value. In our dataset, this translates to transactions smaller than 30,000 INR (or 447 USD using the average INR/USD over the period 2015-2019). As an alternative cut-off, we also use 50,000 INR (or 746 USD). We then construct the stock market participation variables, again aggregated at the pincode year-month level as well as at the investor level to test the variations among different types of investors.

Since the NSE data provides limited demographic details on investors, we supplement it with a dataset from one of the top 5 brokerage houses in India for the same sample period as the NSE data. The brokerage data provides rich demographic detail on *Income* (less than 5 Lakhs, between 5 and 20 Lakhs, and larger than 20 Lakhs), *Occupation* (Public Sector, Housewife, Student, Business & Self-employed, Private Sector, Professionals, Service, Retired, and Other), *Education* (Post Graduate, Graduate, and Other), and *Credit score* (<499, 500-649, 650 - 749, and above 750). It should be noted that the brokerage sample represents a set of relatively large investors, with average daily transaction value of 1.51 million INR or 18,000 USD. However, as shown below, we are able to establish our baseline results on this dataset as well.

2.3.2. Investor-level Measures

As measures of market participation outcomes, we construct the following measures: First, following Barber et al. (2009) we calculate the excess BHR for different time horizons (1, 10, 25, and 140 trading days) as follows:

$$BHR_{S,i,d,D} = \mathbb{I}[Buy = 1]_{S,i,d} \cdot \frac{Price_{S,d+D} - Price_{S,d}}{Price_{S,d}} \tag{3}$$

Where $\mathbb{I}[Buy = 1]_{S,i,d}$ equals 1 if investor i executes a *buy* transaction for stock S on day d, and equals -1 if the transaction is a *sell*. $Price_{S,d(+D)}$ indicates the closing price for stock S on day $d + D$, where D equals 1, 10, 25, or 140. We then calculate the excess buy-and-hand return (BHR) for each transaction by subtracting the market return for the same time horizon from the BHR.[14] Finally, the average excess BHR for each investor in each month is calculated as the weighted average of the excess BHRs for different time horizons across all transactions conducted by the investor in the same month.

Next, we measure *Risk Taking* by calculating the ratio of the number of transactions in risky assets over the total number of transactions per investor-month. A security is classified as risky if the standard deviation of its price is above the median of all traded stocks in the market for that month.

To assess *Portfolio Diversification*, we use a Herfindahl-Hirschman Index (HHI)-based measure, following Koch et al. (2021):

$$\text{Portfolio Diversification}_{i,t} = 1 - \sum_{T} \left(\frac{Turnover_{i,S,t}}{\sum_T Turnover_{i,S,t}}\right)^2 \tag{4}$$

where $Turnover_{i,S,t}$ is the summation of buy value and sell value that investor i traded on security S at month t.

Finally, to measure *Trading Speed*, we calculate the average number of days between consecutive transactions for each investor within the same month. A higher value indicates that the investor

[14] The market return data is directly calculated using the NIFTY 50, a stock market index of 50 of the largest Indian companies listed on the National Stock Exchange.

takes longer to execute two successive transactions.

Table 1 shows that at the individual investor level, the buy-and-hold returns (BHR), are on average negative for all windows and most negative for the 140-day window, suggesting that investors incur losses over the long term. The average risk taking is 0.617 suggesting that 61% of the transactions are in risky assets. The average representative investor maintains a diversified portfolio (Portfolio HHI of 0.573), with an average interval of 4.4 days between consecutive transactions.

TABLE 1 ABOUT HERE

2.4. Validating the UPI Exposure Measure

One of the concerns with the UPI exposure measure may be that other time-varying factors differentially affect high- and low-exposure pincodes. To explore this, in the balance Table 2 we examine whether the UPI exposure measures correlate with ex-ante differences in economic activity (as measured by night-light intensity), transactions, or investor characteristics.

Table 2 shows that high- and low-UPI exposure regions exhibit some variation, but no significant differences in economic activity. Further, our main outcomes of interest, number of transactions and number of retail investors are not significantly different from each other as seen in the balance table. When analyzing individual characteristics in the NSE sample, we find no statistically significant differences in demographic attributes such as age or gender between high- and low-exposure pincodes.

Given the limited investor attributes in the NSE sample, we supplement our analysis by using data from one of the largest brokerages in India, which contains rich demographic details as described in section 2.3.1. Table 2 shows that even across the brokerage sample, there is no discernible variation in income levels, education, credit scores, or occupational categories. Overall, these results provide evidence that UPI exposure is not systematically associated with key investor characteristics or pre-existing economic differences.

TABLE 2 ABOUT HERE

Appendix Table A1 shows that the Bartik exposure is also not correlated with economic activity, number of transactions, number of investors, or the age and gender profile of investors in the ex-ante period. Similarly, the brokerage data confirmed that the investors are similar in terms of age, gender, income, occupation, education and creditworthiness across High- and Low- UPI Bartik areas.

3. Main Results

3.1. Does UPI Adoption lead to increased stock market participation?

In this section, we investigate if pincodes that have higher UPI exposure see an increase in stock market activity following UPI adoption in 2016. Using a classic Difference-in-Difference (DiD) framework, we estimate the following equation:

$$Y_{p,d,t} = \alpha_{d,t} + \gamma_p + \beta \cdot \text{Post} \times \text{UPI Exposure}_p + \varepsilon_{p,d,t} \tag{5}$$

where $Y_{p,d,t}$ represents the *Number of Transactions* or *Number of Investors* in pincode p (in district d) in month t; $UPIExposure_p$ is a time-invariant measure of UPI adoption in pincode p described in section 2; *Post* is a dummy variable that equals 1 in the third quarter of 2016 and thereafter and 0 before. The main coefficient of interest is β, which measures the differential change in stock market activity in each pincode associated with a one-unit increase in UPI Exposure. Pincode fixed effects, γ_p, control for time-variant systematic differences across pincodes and district-month fixed effects, $\alpha_{d,t}$, account for variations in policy and macro-economic conditions at the district-level over time. Standard errors are clustered at the pincode level to account for serial correlation in the dependent variable.

As an alternative estimation, we replace the time-invariant UPI Exposure measure with the time-varying Bartik instrument for UPI adoption by using the following equation:

$$Y_{p,d,t} = \alpha_{d,t} + \gamma_p + \beta \cdot \text{UPI Bartik}_{p,t} + \varepsilon_{p,d,t} \tag{6}$$

where UPI Bartik$_{p,t}$ is the Bartik instrument, as defined in the previous section, with all other variables as described above.

Columns 1 and 2 of Table 3 show the results with the UPI Exposure measure while columns 3 and 4 show results with the UPI Bartik measure. Column 1 shows that one standard deviation increase of the UPI exposure leads to the number of transactions increased by 68 in average for each pincode-month. This translates to 6.1% higher transactions relative to the mean of 1107 (Table 1). The number of investors also increased on average by 7 per month in high-exposure pincodes (column 2), representing a 8.6% increase relative to the mean.

The estimates in columns 3 and 4 in Table 3 suggest that areas more exposed to the UPI shock, saw an average monthly increase of 113 stock transactions and 13 investors relative to the mean of 1107 and 81. Moving from the 25$^{\text{th}}$ percentile of the Bartik exposure to the 75$^{\text{th}}$ percentile is associated with an average monthly increase in 10 transactions and 1 investor, respectively.

TABLE 3 ABOUT HERE

The identifying assumption in the empirical specification above is that the treated and control pincodes would have been on similar trends absent the treatment. To justify this assumption, we estimate the dynamic effects of UPI adoption on stock market participation to ensure there are no pre-trends in our outcome variable before the adoption of UPI. Specifically, we estimate a similar specification to equation (5) using the following equation:

$$Y_{p,d,t} = \alpha_{d,t} + \gamma_p + \sum_{k=q} \beta_k \cdot \mathbb{I}[Quarter = k] \times \text{UPI Exposure}_p + \varepsilon_{p,d,t} \tag{7}$$

where $\mathbb{I}[Quarter = k]$ is a series of indicator variables that take the value of 1 in each quarter, with the quarter when UPI was adopted omitted as the reference period.

Figure 4 shows the dynamic effects by plotting the coefficient estimates of the indicator variables described in equation 7. For each of the dependent variables, the coefficients become positive and significant only in the quarter of the UPI adoption and thereafter, with the maximum effect in the 5th quarter after UPI adoption. While the magnitude of the coefficients slightly diminish after that, they are still positive and significant, suggesting long-run effects of UPI adoption on stock

trading activities.

FIGURE 4 ABOUT HERE

As further robustness, we conduct placebo tests by randomly reassigning UPI exposure across pincodes while maintaining the original exposure distribution. Specifically, we estimate equation (5) 500 times, each time with a randomly shuffled assignment of UPI exposure values across pincodes. We then compare the distribution of these placebo coefficients with our main results. As reported in Appendix Table A2, the average coefficient from these placebo regressions is close to zero and statistically insignificant, suggesting that our main findings are not driven by spurious correlations in the data.

3.2. Identification using Investor-level data

To strengthen our causal interpretation, we address potential time-varying confounders at the pincode level by examining investor-level trading behavior across multiple brokerage accounts. For this test, we turn to proprietary investor-level data from one of the largest brokerage firms in India that allows us to identify whether a brokerage account is associated with an early UPI-adopting bank. If UPI adoption indeed facilitates stock market participation, we expect that the same investor would execute more transactions through accounts linked to early UPI-adopting banks compared to their other accounts. We test this hypothesis using the following specification:

$$Y_{i,b,t} = \alpha_{i,t} + \gamma_b + \beta \cdot \text{Post}_t \times \text{Early Adopter}_b + \varepsilon_{i,b,t} \tag{8}$$

where Y represents the number of transactions by investor i through brokerage account b in month t. *Early Adopter* is an indicator that equals 1 if brokerage account b is associated with an early UPI-adopting bank. *Post* indicates the post-UPI adoption period starting from Q3 2016.

TABLE 4 ABOUT HERE

Table 4 presents strong evidence that UPI adoption increases trading activity. Column 1 uses the broadest sample: all investors who had two or more brokerage accounts at any point during the

sample period (2015-2020). Controlling for time-invariant investor characteristics (investor fixed effects), local economic conditions (district-month fixed effects), and brokerage specific features (broker fixed effects), accounts linked to early UPI-adopting banks see 52.06 additional monthly transactions relative to non-early-adopter accounts for the same investor. This effect persists when we restrict our sample to investors maintaining multiple brokerage accounts simultaneously. Column 2 restricts the sample to only investors who maintained two or more brokerage accounts during each month. This is a more stringent test as it focuses on consistently active multi-account investors. The smaller coefficient (41.63) with similar fixed effects suggests the effect is robust but somewhat smaller in this more selected sample. Most stringently, in Column 3, we include investor-month fixed effects to control for all time-varying investor characteristics, effectively comparing trading activity across different accounts of the same investor in the same month. The smaller but still significant coefficient (13.97) indicates that even when comparing accounts held by the same investor in the same month, those linked to early UPI-adopting banks see more activity. These results strongly suggest that our findings are not driven by local economic conditions or time-varying investor characteristics.

3.3. Identification through Bank Mergers and Digital Platform Comparison

A key identification challenge in our analysis is separating UPI's effect from other bank characteristics. Early-adopting banks may have been more technologically sophisticated overall or may have simultaneously introduced other digital innovations that could affect trading behavior. Additionally, customers who selected these banks might have had stronger technological preferences or trading propensities. To address these concerns, we employ two complementary identification strategies. First, we exploit a natural experiment created by the merger between Canara Bank (an early UPI adopter) and Syndicate Bank (a non-early adopter), which generated exogenous variation in UPI access independent of bank characteristics or customer selection. Second, we compare UPI's impact against State Bank of India's proprietary digital banking platform, YONO, to distinguish the effects of UPI's open banking framework from bank-specific digital capabilities. These tests help isolate UPI's causal effect on trading behavior from other potentially confounding factors. We describe these tests in detail below:

3.3.1. Event study of Canara Bank and Syndicate Bank Merger

"We leverage a bank merger event to examine whether stock market participation increases when a brokerage-associated bank suddenly gains access to UPI through the merger. On August 31, 2019, Canara Bank acquired Syndicate Bank, forming the fourth-largest public lender in India. Prior to the merger, Canara Bank was an early UPI adopter, while Syndicate Bank was not. As a result of the merger, Syndicate Bank immediately gained access to UPI. Despite the merger, investors retained access to brokerage accounts associated with each bank, providing us with a clean setting to examine how enabling UPI affects trading behavior.

We restrict our analysis to a narrow eight-week window around the merger event (four weeks before and after) and examine trading activity at the investor-broker-week level. Our sample includes only transactions executed through brokerage accounts associated with Canara Bank and Syndicate Bank. We aggregate the number of transactions conducted by each investor across the two accounts on a weekly basis and estimate both static difference-in-differences and dynamic event study specifications. Specifically, we estimate the following:

$$Y_{i,b,t} = \alpha_i + \gamma_b + +\theta_t + \beta \cdot \text{Post Merger}_t \times \text{Syndicated Bank}_b + \varepsilon_{i,b,t} \tag{9}$$

where Y is the Number of Transaction made by investor i through brokerage account b at month t. *Syndicated Bank* equals to 1 if for transactions executed via brokerage account associated with the Syndicated Bank. *Post Merger* equals to 1 for transactions occured after the merging date.

TABLE 5 ABOUT HERE

Table 5 presents our results. The static DiD estimates in columns 1 and 3 show that post-merger, Syndicate Bank customers increased their number of transactions by 0.286 (column 1) relative to Canara Bank customers, representing a significant increase in trading activity. This effect remains robust, though smaller in magnitude (0.096), when we include investor-week fixed effects in column 3, which control for time-varying investor characteristics. The dynamic specifications in columns

2 and 4 reveal important patterns in the timing of the effect. First, we observe largely parallel pre-trends in the weeks leading up to the merger, with coefficients close to zero and statistically insignificant in weeks -4 and -3. However, we note a significant pre-merger increase in week -2, suggesting some anticipation effects. Post-merger, the impact on trading activity manifests most strongly in weeks 2 and 3, with increases of 0.768 and 0.451 transactions respectively (column 2). These effects remain significant but are more modest (0.282 and 0.175) when controlling for investor-week fixed effects (column 4). The effects appear to dissipate by week 4, suggesting that the merger's impact on trading activity may be strongest in the immediate aftermath of UPI access.

3.3.2. UPI versus YONO

The YONO test provides a unique opportunity to disentangle the effects of UPI's open banking framework from bank-specific digital capabilities by comparing it against SBI's proprietary digital banking application (YONO). YONO serves as an ideal comparison since it represents a closed banking system that primarily serves SBI customers, in contrast to UPI's interoperable framework that works across banks.

We operationalize this test by first restricting our sample to trading activity in accounts linked to SBI. We then construct two YONO exposure measures at the pincode level analogous to our UPI exposure measure: a value-based measure (columns 1-2 in Table 6) and a volume-based measure (columns 3-4 in Table 6). We restrict our analysis to the period after November 2017 when both YONO and UPI are present. The analysis is at the district-month level and we use a specification similar to our baseline specification in Equation (5):

$$Y_{p,d,t} = \alpha_{d,t} + \beta_1 \cdot \text{UPI Exposure}_p + \beta_2 \cdot \text{Yono Exposure}_p + \varepsilon_{p,d,t} \tag{10}$$

The results in Table 6 show that UPI exposure has a strong and significant effect on retail trading activity even after controlling for YONO presence. Specifically, a one-unit increase in UPI exposure is associated with 12.848 more transactions and 1.219 more investors (columns 1-2) when using the value-based YONO measure. These effects remain robust and slightly larger (13.480

transactions and 1.259 investors) when using the volume-based YONO measure (columns 3-4). In contrast, the YONO effect, while statistically significant in some specifications, is economically small - the coefficient is 0.000 for both outcomes using the value measure, and 0.019 for transactions and 0.002 for investors using the volume measure. The substantially larger magnitude of UPI coefficients compared to YONO coefficients suggests that the effect of UPI on retail trading is not simply capturing the impact of banks' general digital capabilities or their customers' technological sophistication. This result suggests that the open banking framework plays a unique role in influencing investors to participate in the stock market. It also helps allay the concern that our results might be driven by bank specific fundamentals. The specification also helps address another concern: unobservable factors correlated with digitization are driving the stock uptake. Since YONO is likely to be correlated with unobservable factors determining digitization, the weak and small effects on the YONO coefficient help alleviate these concerns.

Table 6 About Here

4. Mechanisms

In this section, we examine three key mechanisms through which UPI influences stock market participation. First, UPI reduces friction in fund transfers by enabling instant, 24/7 transfers between bank accounts and trading/demat accounts. This eliminates delays associated with traditional methods like National Electronic Funds Transfer (NEFT) and Real-Time Gross Settlement (RTGS), which operate in batches or require minimum transaction amounts.[15] Second, UPI lowers transaction costs, as it offers zero or minimal fees compared to NEFT and RTGS, which impose tiered charges based on transaction value.[16] Unlike these systems, which typically require access to internet banking or a bank website, UPI provides a faster, more convenient real-time payments directly through a mobile app, making it more user friendly and ideal for small, everyday transactions. Furthermore, users can link multiple bank accounts to a single UPI app, allowing them

[15]NEFT is a system for transferring funds electronically between bank accounts in batches and thus takes some time to settle. RTGS allows for immediate, individual fund transfers but is usually used for large, high-value transactions and thus has a minimum transaction amount.

[16]For instance, RTGS transactions require a minimum of INR 2 lakh, with fees ranging from INR 24.50 to INR 49.50 plus GST, while NEFT fees start at INR 2.50 plus GST for smaller transfers.

to choose which account to use for a payment easily. Finally, UPI strengthens the digital financial ecosystem, fostering familiarity with mobile transactions. As users grow comfortable making everyday payments via UPI – such as purchases from local merchants or peer-to-peer transfers – they become more inclined to explore digital investment platforms. This familiarity reduces psychological barriers to stock market participation and promotes greater financial inclusion.

We investigate each of these mechanisms in detail below.

4.1. Reduction in Transaction Costs

One of the primary benefits of UPI is the reduction in transaction costs arising from the immediacy and convenience of fund transfers. Traditional banking channels like NEFT or checks involve delays, banking hour restrictions, and often higher fees. When investors spot market opportunities, especially during sharp market movements, the ability to instantly transfer funds to their trading account becomes crucial. UPI removes these frictions by enabling 24/7, instant, and low-cost transfers. This reduction in transaction costs is particularly valuable during market stress events when timing is critical and the opportunity cost of delayed execution is high.

To test this mechanism, we use high-frequency time stamped data from the Bombay Stock Exchange and examine trading behavior in a 12-hour window around two flash crash events on the Bombay Stock Exchange on September 11, 2019, and March 12, 2020. On September 11, 2019, the Indian stock market faced its worst day of the year, with the BSE Sensex[17] falling 793 points and erasing 3.3 trillion INR in investor wealth. The decline was driven by policy concerns, including a proposed increase in the public shareholding threshold, a tax surcharge on high-income earners affecting foreign portfolio investors, and a lack of economic stimulus. On March 12, 2020, markets experienced another sharp fall as the Sensex plunged 2,919 points (8.18%) and the Nifty 50 dropped 868 points (8.30%) due to global fears of a recession sparked by the COVID-19 pandemic and its designation as a global health crisis by the World Health Organization. [18]

To analyze how time-sensitive investor reactions to significant market movements vary with

[17] The BSE Sensex is a free-float market-weighted stock market index of 30 companies listed on the Bombay Stock Exchange.

[18] See links 1 and 2 for both details on each crash.

differing UPI exposures, we calculate the trading activities of each active investor during the 12 trading hours before and after each market crash. To address concerns that observed patterns may be specific to a single event, we estimate a model that incorporates data from both crashes. Specifically, we estimate the following equation:

$$Y_{i,h} = \delta_i + \gamma_h + \beta \cdot \text{UPI Exposure}_i \times \text{Post Crash}_h + +\varepsilon_{i,h} \tag{11}$$

where Y measures the number of transactions executed by investor i in hour h, UPI Exposure is the UPI Exposure at the pincode where the investor accomodates. Post Crash is a dummy variable for 12 trading hour window that takes the value 1 for after the crash and 0 before,δ_i and γ_h are investor and hour fixed effects.

The key coefficient β measures whether being exposed to UPI show higher trading activity in the critical hours following a flash crash. We would expect $\beta > 0$ if UPI's reduction in transaction costs enables investors to better respond to market opportunities. For identification, use multiple flash crash events and exploit the fact that the same investor might have both UPI and non-UPI accounts.

TABLE 7 ABOUT HERE

We find consistent significant positive relationship between UPI exposure and trading activity in the aftermath of flash crash events on the Bombay Stock Exchange. The interaction terms between Post Crash and UPI Exposure is consistently positive and significant across all specifications, for both combing or separate the two events, indicating that investors in regions with higher UPI penetration engage in more transactions and trade across a greater number of tickers after market crashes.

These findings suggest that UPIs ability to reduce transaction costs enables investors to respond more efficiently to time-sensitive market opportunities, especially during periods of heightened market stress. The results highlight the critical role of digital payment systems like UPI in enhancing market efficiency and resilience, particularly in the context of emerging economies with rapidly evolving financial infrastructures.

4.2. Lower Entry Barriers

A second mechanism through which UPI affects stock market activity is by reducing entry barriers to stock market participation by enabling easier and more flexible handling of small transactions. Before UPI, small investors faced multiple frictions: minimum balance requirements in trading accounts, cumbersome fund transfer processes, and psychological barriers around committing large sums. UPI's ability to instantly transfer small amounts reduces these frictions - investors can start with modest investments, add funds incrementally, and manage their trading account balance more dynamically. This particularly benefits small investors who might prefer to "test the waters" with smaller amounts before making larger commitments, or those who receive income in smaller, frequent installments rather than large lump sums.

To test this mechanism, we examine trading patterns of small investors in high vs low UPI-exposed pincodes using the following variation of the baseline specification:

$$Small_Trading_{p,d,p,t} = \alpha_{d,t} + \gamma_p + \beta \cdot \text{Post} \times \text{UPI Exposure}_p + \varepsilon_{p,d,p,t} \tag{12}$$

where $Small_Trade_{p,d,p,t}$ represents the *Number of Transactions* by Small Investors and *Number of Small Investors* at the pincode p at month t. The key coefficient β captures whether UPI exposure particularly benefits small-value trading.

Table 8 About Here

The results highlight that UPI exposure significantly reduces entry barriers for small investors, facilitating increased participation in stock market activity. Table 8 Panel A shows that small investors in high-UPI-exposure pincodes exhibit a higher number of transactions following the implementation of UPI. In contrast, the impact for non-small investors is notably smaller. Panel B further confirms this trend, showing a significantly higher number of small investors entering the market in UPI-exposed areas. The significant differences between small and non-small investors, as indicated by the t-tests, underscore that UPI's benefits are particularly pronounced for smaller-value transactions, allowing individuals to engage in incremental investments and fostering broader financial inclusion.

4.3. Digital Infrastructure

Finally, the digital ecosystem mechanism suggests that UPI's impact on stock market participation operates through broader digital financial literacy and network effects. When consumers regularly use UPI for everyday transactions like paying local merchants, ordering food, or splitting bills with friends, they develop familiarity with digital financial interfaces and build trust in electronic payment systems. This daily exposure reduces the cognitive and psychological barriers to trying more complex digital financial services like stock trading. The mechanism is self-reinforcing - as more merchants and consumers in a local area adopt UPI, the network becomes more valuable for all participants, creating social learning opportunities where individuals observe peers successfully using digital financial services. This peer effect and the development of digital financial capabilities could naturally extend to stock market participation, particularly given that many modern trading platforms share similar user interface elements and security features with UPI payment apps.

To test this digital ecosystem mechanism, we compare trading in urban versus rural areas since they differ systematically in the density of UPI-accepting merchants, smartphone penetration, and peer networks. We implement this test by running the baseline regression in equation 5 for two sub-samples - urban and rural areas.[19]

Table 9 About Here

The results provide strong evidence that UPI's impact on stock market participation is amplified through the digital ecosystem, particularly in urban areas where digital infrastructure is more developed. The interaction terms show a significantly larger effect on the number of transactions in urban areas compared to rural areas, with a t-test difference of 315.215 ($p < 0.01$). Similarly, the number of investors increases more substantially in urban areas relative to rural areas, with a significant t-test difference of 32.414 ($p < 0.01$). These results highlight the role of urban digital infrastructure in driving greater stock market engagement. This supports our conjecture that urban areas with high digital adoption support the digital ecosystem mechanism.

[19]Post 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.

Overall, our empirical tests identify three distinct but complementary channels through which UPI enhances stock market participation - UPI simultaneously reduces transaction frictions for active investors responding to market events, lowers barriers to entry for small investors, and leverages existing digital payment networks to build trust in electronic financial services.

5. Consequences

In this section, we investigate whether the adoption of UPI have real implications for the investors in terms of both excess returns and trading behaviors. For trading behaviors, we analyze whether UPI adoption affects risk-taking, portfolio diversification, and trading speed, particularly for small investors. We first estimate an equation similar to 5, but at the investor level, to analyze the general effects of UPI at the investor level. This analysis uses dependent variables that measure excess returns and trading behaviors at the investor level, as described in Section 2. To isolate the specific effects of UPI on small investors, we employ a triple interaction model by incorporating an indicator variable for small investors into the DiD model. Specifically, we estimate the following two equations:

Specifically, we estimate the following two equations:

$$Y_{i,p,d,t} = \kappa_i + \lambda_{d,t} + \beta \cdot \text{Post} \times \text{UPI Exposure}_p + \varepsilon_{i,d,t} \tag{13}$$

and

$$\begin{aligned} Y_{i,p,d,t} = \kappa_i + \lambda_{d,t} + \beta_0 \cdot \text{Post} \times \text{UPI Exposure}_p + \beta_1 \cdot \text{Small} + \\ \beta_2 \cdot \text{Small} \times \text{UPI Exposure}_p + \beta_3 \cdot \text{Post} \times \text{Small} + \\ \beta_4 \cdot \text{Post} \times \text{UPI Exposure}_p \times \text{Small} + \varepsilon_{i,p,d,t} \end{aligned} \tag{14}$$

where $Y_{i,d,t}$ represents the described dependent variables for investor i, residing in district d at month t. κ denotes the investor-level fixed effects, and λ represents the district-month fixed effects. All other variables are described in Section 2.

We present the estimation results in both Table 10 and 11, with 10 displaying the results for excess return and 11 showing the results for trading behaviors. As shown in the frist four columns in 10 the interaction terms for UPI Exposure and Post captures the general effect of UPI adoption on excess returns. While the coefficients for shorter holding periods (1, 10, and 25 trading days) are small and not statistically significant, the negative and significant coefficient for the 140-trading-day horizon suggests a decline in long-term returns following UPI adoption. This pattern indicates that while the broader investor population does not experience immediate changes in returns, longer-term performance may be negatively affected, potentially due to over-trading or misaligned investment strategies driven by the adoption of UPI.

In addition, for small investors, the triple interaction terms consistently demonstrates a significant and positive effect on excess returns for short- and medium-term horizons, specifically over 1, and 10 trading days. However, for longer holding periods (25 or 140 trading days), the effect becomes either insignificant or negatively significant. This suggests that while small investors initially benefit from UPI adoption through enhanced trading strategies or market access, their long-term performance deteriorates, potentially due to over-trading or suboptimal investment choices.

Table 11 further examines the impact of UPI adoption on trading behaviors, including risk-taking, diversification, and trading speed. In the first three columns, the interaction term between UPI Exposure and Post reflects the general effect of UPI adoption. The results show a significant reduction in risk-taking and a substantial improvement in portfolio diversification, as evidenced by the negative coefficients in column 1 and the positive coefficient in column 2, respectively. These findings suggest that UPI adoption encourages broader and more cautious investment strategies among investors overall. However, the coefficient for trading speed is small and insignificant, indicating that UPI adoption does not lead to immediate changes in trading frequency or efficiency for the general investor population.

Interestingly, for small investors, the triple interaction terms reveal notable differences in trading behaviors. While UPI adoption is associated with increased trading speed for small investors, it reduces portfolio diversification, suggesting a shift towards more concentrated portfolios. Additionally, the reduction in risk-taking is more pronounced for small investors, highlighting that UPI adoption has a stronger impact on curbing speculative behavior in this group. These results

indicate that UPI adoption leads to distinct behavioral trade-offs for small investors, promoting faster trading but potentially less diversified portfolios.

6. Conclusion

This paper provides novel evidence on how payment infrastructure shapes retail investor participation in financial markets. By exploiting the staggered adoption of UPI across Indian banks, we establish that digital payment technology can significantly lower barriers to stock market participation. Our findings reveal that high UPI-exposure regions experience a 17.8% increase in monthly transactions and a 25% increase in active investors relative to low-exposure regions, highlighting the substantial economic impact of reducing payment frictions.

Our analysis identifies three distinct mechanisms through which payment infrastructure affects market participation. First, by enabling instant fund transfers, UPI allows investors to respond more quickly to market events, as evidenced by increased trading activity during flash crashes. Second, by reducing minimum investment constraints and simplifying account funding, UPI particularly benefits small investors, leading to a democratization of market access. Third, the effectiveness of UPI adoption is amplified through network effects within the broader digital ecosystem, with stronger impacts in urban areas having greater digital penetration.

However, our findings also reveal potential downsides of reduced market frictions. While UPI adoption increases market participation, it appears to encourage potentially problematic trading patterns among small investors. These investors exhibit reduced portfolio diversification and negative excess returns over longer horizons, suggesting that easier market access may not necessarily translate into better investment outcomes.

These results have important implications for market design and financial policy. While digital payment infrastructure can effectively democratize market access, our findings suggest that complementary interventions – such as financial education or "nudges" toward diversification – may be necessary to ensure that increased market participation leads to favorable investor outcomes. More broadly, our study demonstrates how technological innovation in market infrastructure can

significantly alter patterns of retail trading and market participation, while potentially introducing new challenges for investor protection.

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Figure 1: Geographic Variation in UPI Exposure

The two maps plot the geographic distribution of UPI exposure (left) and UPI Bartik (right) across all pincodes in India. UPI Exposure is defined as the ratio of deposits for early adopter banks to total deposits as defined in Equation (1). The classification of early adopter banks is as of November 2016 and is provided by the Government of India. Bank-branch level deposit data is from Basic Statistical Returns (BSR) provided by the Reserve Bank of India. UPI Bartik uses the national-level variation in UPI adoption over time and interacts it with the relative importance of early UPI adoption in a given pincode. The measures are averages across all months over our sample periods. Brighter colors indicate pincodes with higher UPI exposure.

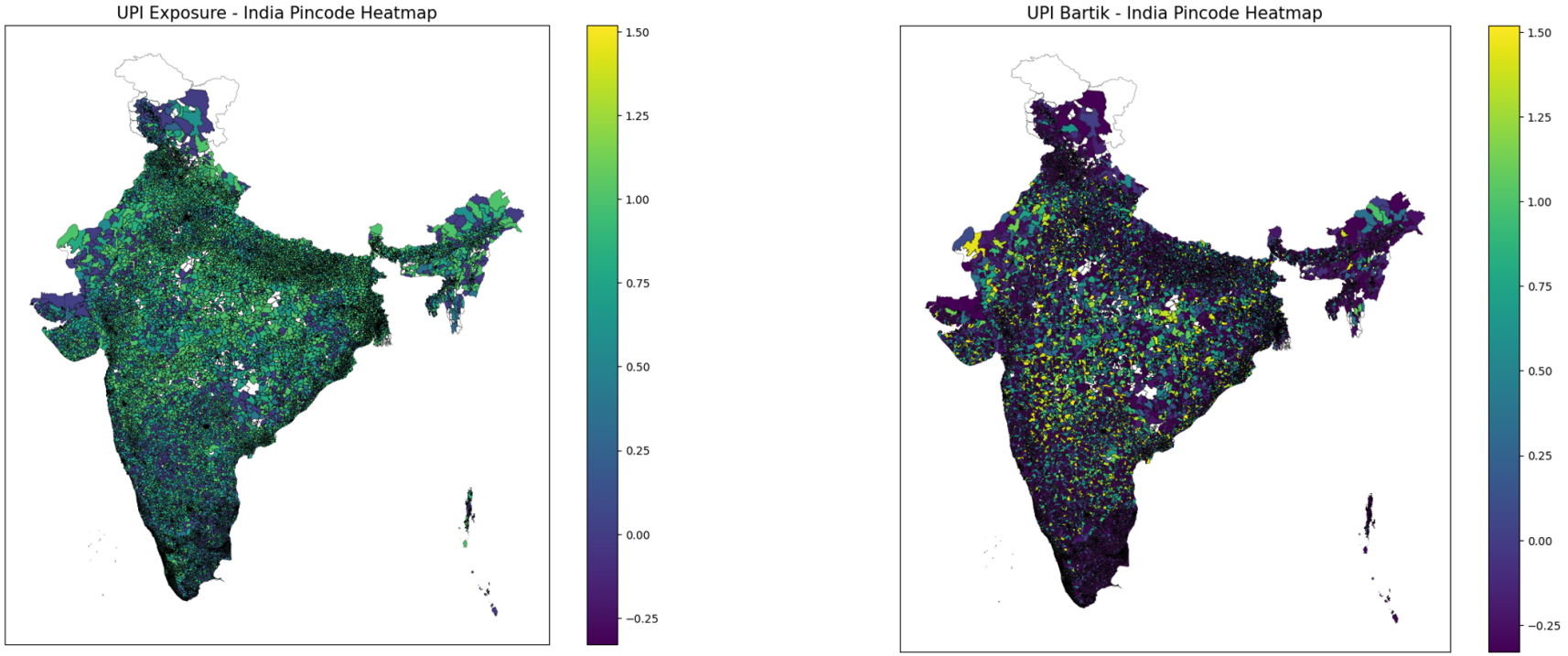


Figure 2: Stock Market Participation over Sample Period

This figure shows the number of transactions by retail investors (blue bold line) and number of retail investors (red dashed line), over time, averaging across all the pincodes. The data is at monthly frequency and covers the period first quarter of 2015 to first quarter of 2020.

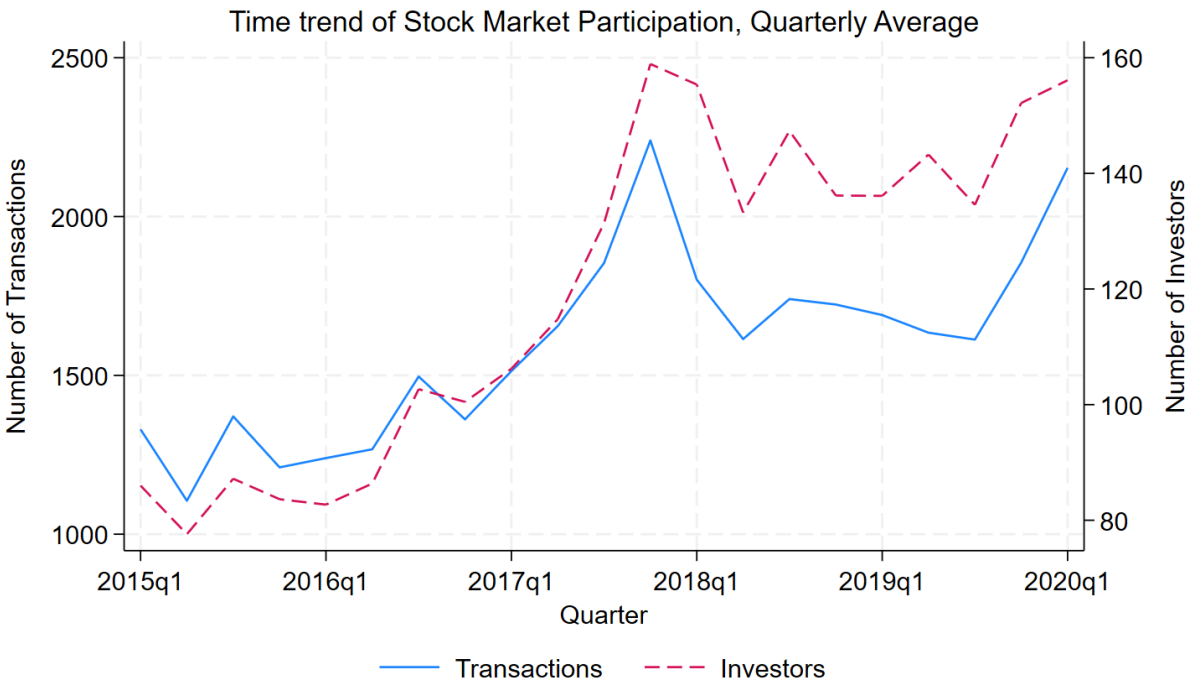
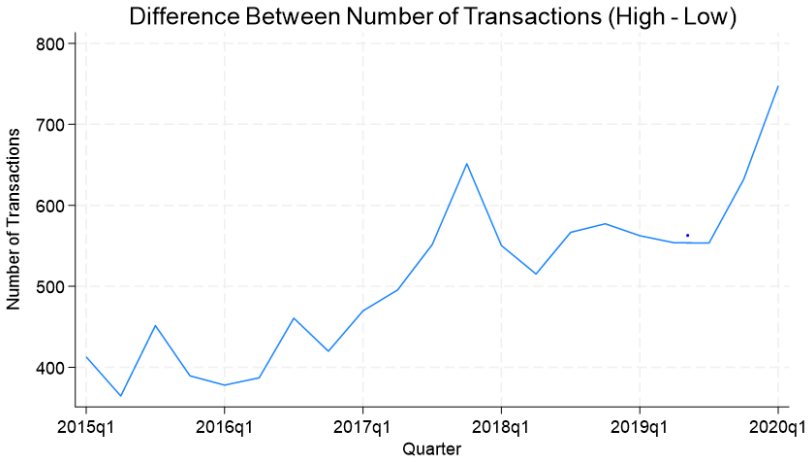


Figure 3: UPI and Stock Market Participation

This figure illustrates the difference in the average number of retail transactions (left) and retail investors (right) between high- and low-UPI exposure pincodes. We first aggregate the trading data, that is available on a monthly frequency from first quarter of 2015 to first quarter of 2020, to the pincode level and then compute the difference between the two groups. High UPI-exposure pincodes have values of UPI exposure above the median and low UPI-exposure pincodes have values equal or below the median.



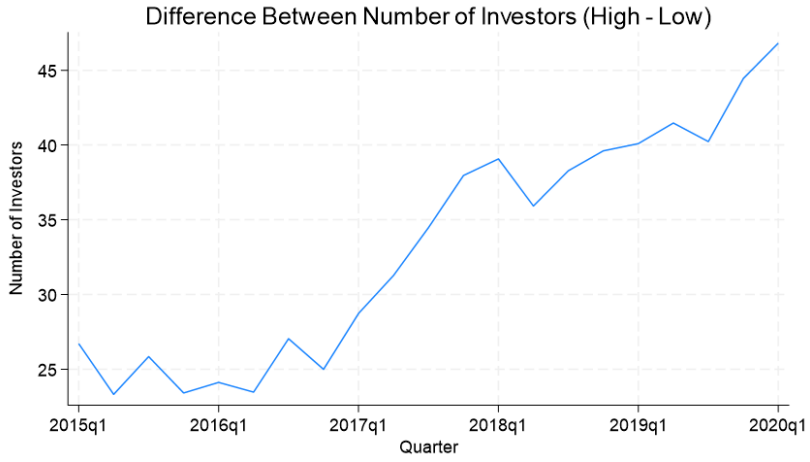


Figure 4: Dynamic Effects of UPI on Stock Market Participation

This figure presents treatment dynamics as a test of parallel trends using the specification in equation 5 for the number of retail transactions (left) and retail investors (right). The underlying data, aggregated at the pincode level, is at a quarterly frequency from Q1 2015 to Q4 2019. Each dot represents the point estimate, with vertical lines indicating 95% confidence intervals. The regression includes pincode and district-month fixed effects, with standard errors that are heteroskedasticity-robust and clustered at the pincode level. The dashed red vertical line marks the pre-treatment quarter (Q2 2016) and the solid blue line marks September 2017, when a circular released by the Reserve Bank of India strengthened the open banking system.

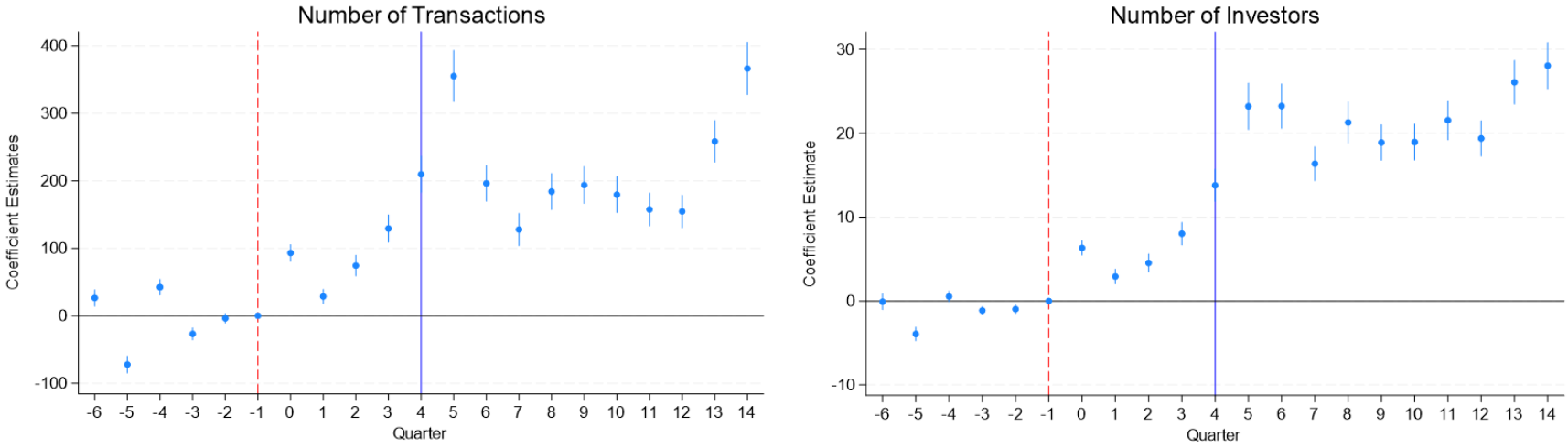


Figure 5: Treatment Dynamics of Retail Trading Around the Canara-Syndicate Bank Merger

This figure presents the treatment dynamics around the acquisition of Syndicate Bank (a late UPI adopter) by Canara Bank (an early UPI adopter) on August 31, 2019, using the specification in equation 9. The dependent variable is the total number of retail transactions at the investor-broker level with weekly frequency, covering the first week of August 2019 (4 weeks prior to acquisition) to the last week of September 2019 (4 weeks after acquisition). Each dot represents the point estimate, with vertical lines indicating 95% confidence intervals. The regression includes investor, broker, and week fixed effects, with standard errors that are heteroskedasticity-robust and clustered at the investor level. The dashed vertical line denotes the pre-treatment week.

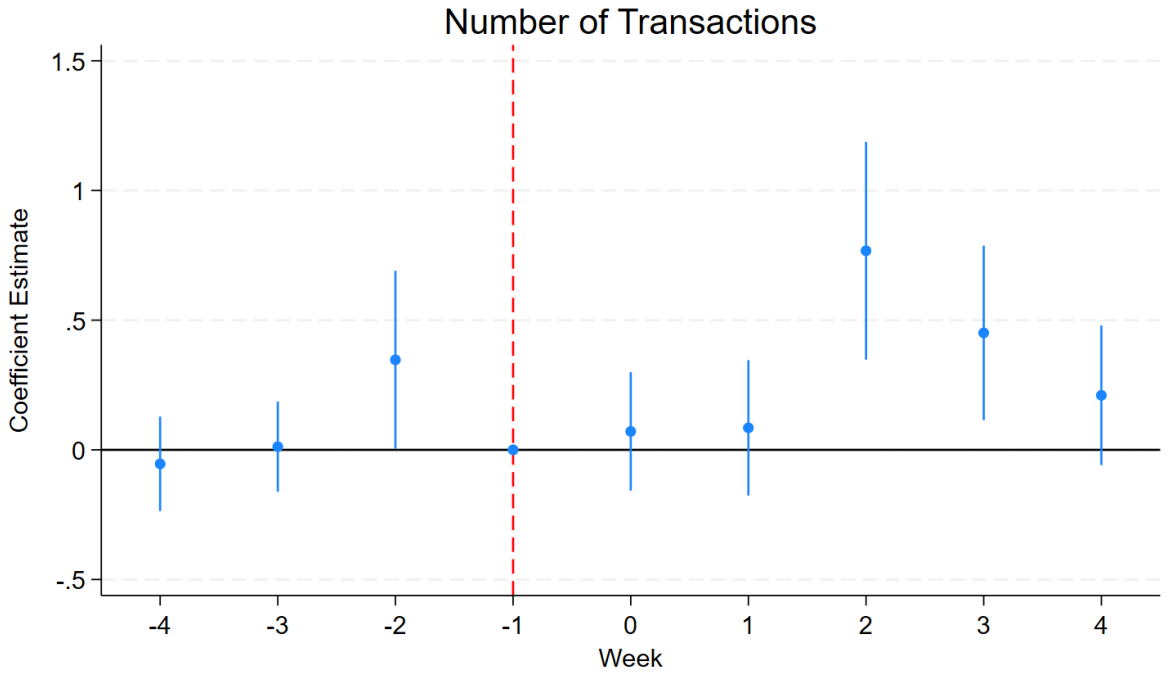


Figure 6: Dynamic Effects of UPI on Stock Market Participation – Rural vs Urban Pincodes

This figure presents treatment dynamics using the specification in equation 5 for the number of retail transactions (left) and the number of retail investors (right) in rural (blue dots) and urban (red triangles) areas. The underlying data, aggregated at the pincode level, is at a quarterly frequency from Q1 2015 to Q4 2019. Each dot (or triangle) represents the point estimate, with vertical lines indicating 95% confidence intervals. The regression includes pincode and district-month fixed effects, with standard errors that are heteroskedasticity-robust and clustered at the pincode level. The dashed vertical line marks the pre-treatment quarter (Q2 2016).

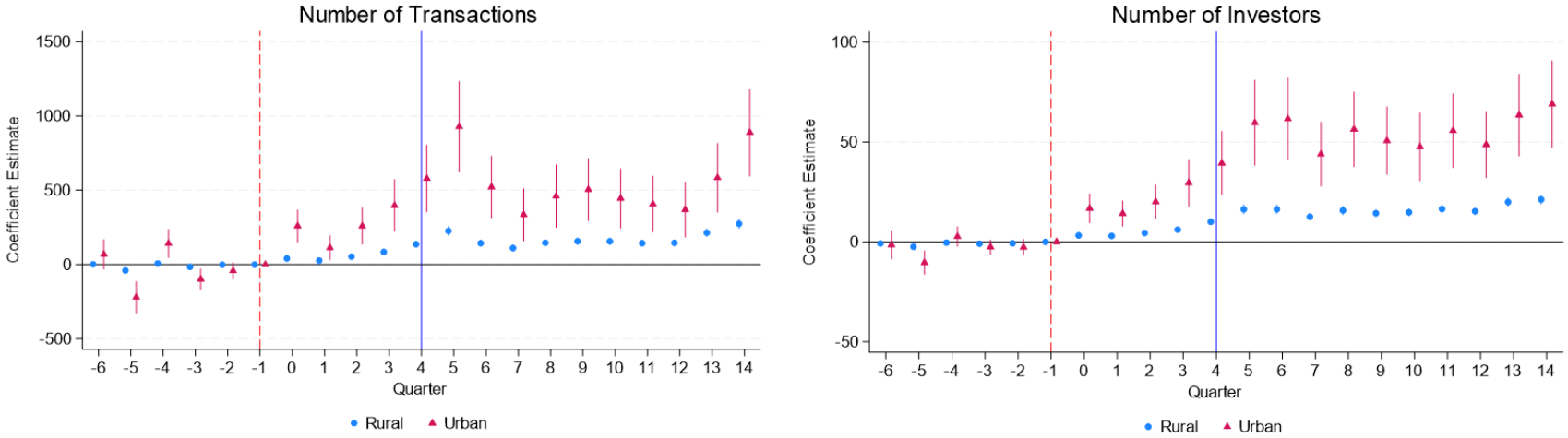


Figure 7: Dynamic Effects of UPI on Stock Market Participation – Small vs Large Investors

This figure shows the treatment dynamics using the specification in equation 5 for the total number of small (blue dots) and large (red squares) retail investors. We consider an investor to be a small investor if his/her total transaction value for a particular month is in the bottom 30 percent of transactions in terms of trading value, which translates to transactions smaller than 30,000 INR (or 447 USD using the average INR/USD over the period 2015-2019). Underlying observations are at the pincode level at the quarterly frequency for the period Q1 2015 to Q4 2019. Each dot shows the point estimate, with the vertical lines indicate the 95% confidence intervals. Pincode and district-month fixed effects are included. Standard errors are heteroskedasticity robust and clustered at the pincode level. The dashed vertical line marks the pre-treatment quarter (Q2 2016).

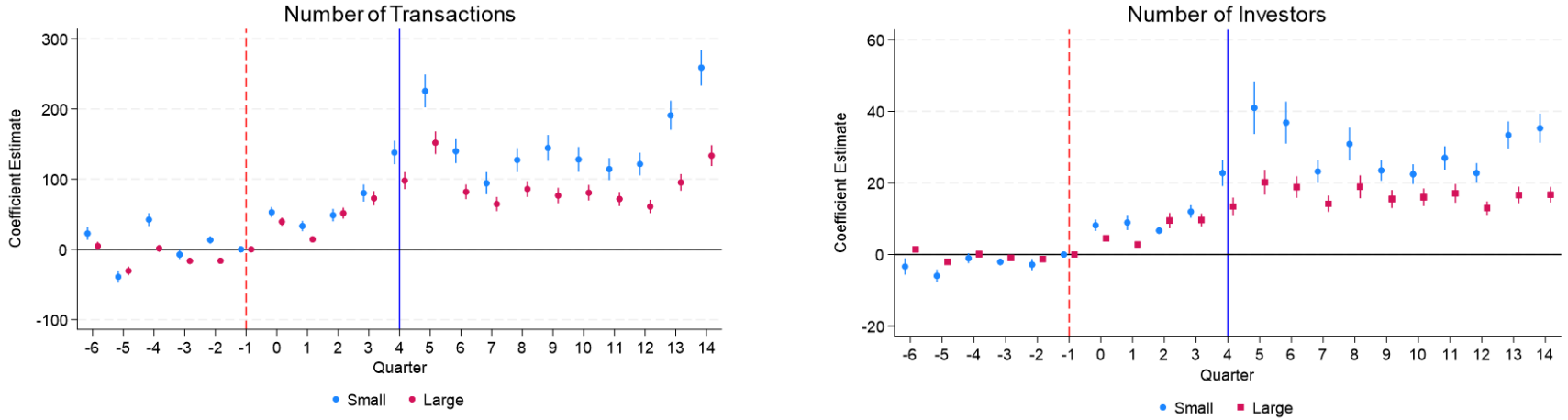


Table 1: Summary Statistics

This table reports the summary statistics for the key variables in our analysis.

Variable	N	Mean	S.D.	Min	P25	Median	P75	Max
Pincode-month level								
UPI Exposure	1,135,393	0.650	0.347	0	0.433	0.764	0.957	1
UPI Bartik	1,124,040	0	1	-0.288	-0.288	-0.288	-0.275	9.102
Post	1,135,393	0.639	0.480	0	0	1	1	1
Number of Transactions	1,124,014	1107.816	2932.836	0	55	205	653	26973
Number of Investors	1,124,051	81.095	217.208	0	5	16	47	2060
Investor-month level								
BHR1	108,045,406	-0.013	0.105	-0.472	-0.059	-0.012	0.025	0.577
BHR10	108,016,403	-0.068	0.342	-1.414	-0.239	-0.054	0.090	1.336
BHR25	107,971,591	-0.147	0.668	-2.709	-0.506	-0.140	0.186	2.328
BHR140	100,480,494	-0.628	1.602	-7.639	-1.332	-0.507	0.024	5.130
Risk Taking	108,131,872	0.617	0.200	0	0.548	0.650	0.729	1
Portfolio Diversification	108,131,872	0.573	0.168	0	0.502	0.582	0.625	1
Trading Speed	108,131,872	4.366	2.203	0	3.349	4.426	5.244	30

Table 2: Balance Test - UPI Exposure

This table compares ex-ante differences across high-exposure and low-exposure pincodes in the following variables: Levels of economic activity as proxied by night-light intensity; Stock market activity as proxied by the Number of Transactions and Number of Investors; Investor Demographics as proxied by Age, Gender, Income, Occupation, Education, and Credit Score. The Age and Gender details are available in both the NSE data and the brokerage data whereas the other demographic details are available only in the brokerage data.

	(1)		(2)		(1-2)
Variable	High UPI Exposure		Low UPI Exposure		Pairwise t-test
	N	Mean/(SE)	N	Mean/(SE)	Mean Difference
Pincode: NSE Sample					
Economic Activity	9,306	10.684	9,307	8.059	2.625
		(13.894)		(13.323)	
Number of Transactions	204,754	1103.085	204,732	805.672	297.413
		(3047.097)		(2463.475)	
Number of Investors	204,754	78.103	204,732	55.675	22.428
		(222.424)		(175.743)	
Investor: NSE Sample					
Age	659,504	37.768	659,646	37.998	-0.23
		(12.849)		(13.253)	
Female	659,504	0.119	659,646	0.134	-0.015
		(0.324)		(0.341)	
Investor: Brokerage Sample					
Age	186,528	47.755	189,338	47.855	-0.100
		(11.930)		(112.137)	
Female	186,528	0.250	189,338	0.254	-0.004
		(0.433)		(0.435)	
Income: $<$ 5 LAC	186,528	0.430	189,338	0.456	-0.026
		(0.495)		(0.498)	
Income: 5 LAC - 20 LAC	186,528	0.396	189,338	0.391	0.006
		(0.489)		(0.488)	
Income: $>$ 20 LAC	186,528	0.174	189,338	0.153	0.020
		(0.379)		(0.360)	
Occupation: Public Sector	186,528	0.037	189,338	0.031	0.006
		(0.189)		(0.174)	
Occupation: Housewife	186,528	0.124	189,338	0.129	-0.005
		(0.330)		(0.336)	
Occupation: Student	186,528	0.013	189,338	0.013	0.000
		(0.114)		(0.114)	
Occupation: Business & Self-employed	186,528	0.090	189,338	0.095	-0.005
		(0.285)		(0.293)	
Occupation: Private Sector	186,528	0.223	189,338	0.225	-0.002
		(0.416)		(0.417)	
Occupation: Professionals	186,528	0.162	189,338	0.161	0.002
		(0.369)		(0.367)	
Occupation: Service	186,528	0.094	189,338	0.086	0.008
		(0.292)		(0.280)	
Occupation: Retired	186,528	0.079	189,338	0.080	-0.001
		(0.270)		(0.272)	
Occupation: Other	186,528	0.178	189,338	0.180	-0.002
		(0.382)		(0.384)	
Education: Post Graduate	186,528	0.095	189,338	0.092	0.003
		(0.293)		(0.288)	
Education: Graduate	186,528	0.359	189,338	0.358	0.001
		(0.480)		(0.479)	
Education: Other	186,528	0.546	189,338	0.551	-0.004
		(0.498)		(0.497)	
Credit Score: $<$ 499	186,528	0.183	189,338	0.192	-0.009
		(0.387)		(0.394)	
Credit Score: 500 - 649	186,528	0.024	189,338	0.024	0.000
		(0.153)		(0.153)	
Credit Score: 650 - 749	186,528	0.042	189,338	0.043	-0.001
		(0.201)		(0.204)	
Credit Score: $>$ 750	186,528	0.751	189,338	0.740	0.010
		(0.433)		(0.438)	

Table 3: UPI and Stock Market Participation

This table presents the difference-in-difference (DiD) and Bartik instrument estimates for the impact of UPI exposure on stock market participation at the regional (pincode) level. Observations are at the pincode-month level and span the period January 2015 to January 2020. The dependent variable in columns 1, and 3 is the *Number of Transactions* at each pincode-month, and the dependent variable in columns 2, and 4 is the *Number of Investors*. UPI exposure is a continuous variable that measures the regional exposure, defined as in equation 1.Post is a dummy, which takes value 1 from Q3 2016 onward. Bartik instrument is defined in equation 2. Pincode and district-month effects are included as indicated. Pincode-clustered standard errors are reported in parentheses

DV	Number of Transactions (1)	Number of Investors (2)	Number of Transactions (3)	Number of Investors (4)
UPI Exposure X Post	197.761***	20.323***		
	(11.706)	(1.060)		
UPI Bartik			113.149***	13.410***
			(4.256)	(0.366)
Pincode FE	Y	Y	Y	Y
District-Month FE	Y	Y	Y	Y
N	1,121,351	1,121,396	1,121,351	1,121,396
Adj. R^2	0.964	0.964	0.965	0.967

Table 4: UPI and Stock Market Participation: Investor-Brokerage Analysis

This table presents the difference-in-difference (DiD) estimates for the impact of UPI adoption among banks on stock market participation at the investor level. Observations are at the investor-month level and span the period January 2015 to January 2020. The dependent variable is *Number of Transaction* (at the investor level) across all columns. In column 1, we restrict the sample to investors with two or more brokerage account during the sample period; and in columns 2 and 3, the sample is further restrict to investors with two or more brokerages at each month. Early UPI Enabled Brokerages is a dummy variable that equals to 1 if the brokerage account associated bank is an early UPI adopter. Post is a dummy, which takes value 1 from Q3 2016 onward. Investor, district-month, broker fixed effects are included as indicated in columns 1, and 2; and district-month, broker, investor-month fixed effects are included in column 3. Investor-clustered standard errors are reported in parentheses.

Sample	Investor with two or more brokers during entire sample period	Investor with two or more brokers in each month	
DV	Number of Transactions		
Post X Early UPI Enabled Brokerage	52.060**	41.626*	13.968**
	(21.218)	(23.568)	(6.846)
Investor FE	Y	Y	
District-Month FE	Y	Y	Y
Broker FE	Y	Y	Y
Investor-Month FE			Y
N	54,946,106	15,264,352	15,078,443
Adj. R^2	0.303	0.294	0.341

Table 5: Event Study of Canara Bank (early adopter bank) and Syndicate Bank Merger

This table presents the average difference-in-difference (DiD) estimates, as well as the dynamic effects for the impact of UPI enabling via bank merging on market participation at the investor level. Observations are at the investor-broker-week level and span the period of first week in August 2019 to the last week of September 2019. The dependent variable is *Number of Transaction* (at the investor-broker level) across all columns, while in columns 1, and 3we estimate the simple DiD estimator, while in columns 2 and 4, we estimate the dynamic effects around the 4-week window before and after the merging. Treat is a dummy variable that equals to 1 if the brokerage account associated bank is Syndicated bank. Post is a dummy, which takes value 1 from first week of September 2019. Investor, broker, and week fixed effects are included as indicated in columns 1, and 2; and broker, investor-week fixed effects are included in column 3, and 4. Investor-clustered standard errors are reported in parentheses.

DV	Number of Transactions			
	(1)	(2)	(3)	(4)
Syndicated Bank X Post Merger	0.286**		0.096**	
	(0.116)		(0.040)	
Syndicated Bank X Before Merger (Wk - 4)		-0.054		0.011
		(0.093)		(0.068)
Syndicated Bank X Before Merger (Wk - 3)		0.012		0.103
		(0.089)		(0.071)
Syndicated Bank X Before Merger (Wk - 2)		0.347**		0.191**
		(0.175)		(0.079)
Syndicated Bank X Post Merger (Wk 0)		0.071		0.043
		(0.117)		(0.081)
Syndicated Bank X Post Merger (Wk + 1)		0.085		0.059
		(0.133)		(0.086)
Syndicated Bank X Post Merger (Wk + 2)		0.768***		0.282***
		(0.214)		(0.094)
Syndicated Bank X Post Merger (Wk + 3)		0.451***		0.175**
		(0.172)		(0.080)
Syndicated Bank X Post Merger (Wk + 4)		0.210		0.075
		(0.137)		(0.087)
Investor FE	Y	Y		
Broker FE	Y	Y	Y	Y
Week FE	Y	Y		
Investor-week FE			Y	Y
N	123,630	123,630	123,630	123,630
Adj. R^2	0.637	0.637	0.709	0.709

Table 6: UPI Expsoure vs. Yono

This table shows the comparison of UPI exposure with YONO, a digital banking platform launched by the State Bank of India (SBI) in 2017. We first restrict our sample to trading activity in accounts linked to SBI. We constructing two YONO exposure measures at the pincode level analogous to our UPI exposure measure: a value-based measure (columns 1-2) and a volume-based measure (columns 3-4 in Table 6). The analysis is conducted at the district-month level using a specification similar to our baseline specification in equation (5)

Yono Measure	Value		Volume	
	Number of Transactions	Number of Investors	Number of Transactions	Number of Investors
	(1)	(2)	(3)	(4)
UPI Exposure	12.848***	1.219***	13.480***	1.259***
	(1.001)	(0.087)	(0.821)	(0.071)
Yono	0.000*	0.000	0.019***	0.002***
	(0.000)	(0.000)	(0.007)	(0.001)
District-Month FE	Y	Y	Y	Y
N	1,014,920	1,015,360	1,014,920	1,015,360
Adj. R^2	0.221	0.295	0.210	0.285

Table 7: Mechanisms: Reduction in Transaction Cost

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation during market crash. Observations are at the investor-hour level and span 12-trading-hour-window before and after the two stock market crashes at the Indian stock market. The dependent variable in columns 1, 3, and 5 is the *Number of Transactions* at each investor-hour, while the dependent variable in columns 2, 4, and 6 is the *Number of Investors*. Columns 1, and 2 represents the average effects across two market crashes, while columns 3(5), and 4(6) are the corresponding dependent variables for the event in 2019, and 2020. UPI exposure is a continuous variable that measures the regional exposure, defined as in equation 1. PostCrash is a dummy, which takes value 1 for the 12-hour post market crash. Investor and hour effects are included as indicated. Investor-clustered standard errors are reported in parentheses

BSE Test

Event	2019 & 2020		2019		2020	
DV	Number of Transactions	Number of Tickers Traded	Number of Transactions	Number of Tickers Traded	Number of Transactions	Number of Tickers Traded
	(1)	(2)	(3)	(4)	(5)	(6)
Post Crash X UPI Exposure	0.007**	0.003***	0.004**	0.002*	0.010***	0.004***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Investor FE	Y	Y	Y	Y	Y	Y
Hour FE	Y	Y	Y	Y	Y	Y
N	16,113,715	16,183,280	6,042,175	6069809	10,071,520	10,113,454
Adj. R^2	0.117	0.133	0.164	0.184	0.116	0.132

Table 8: Mechanisms: Lower Entry Barries

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation at the regional (pincode) level. Observations are at the pincode-month level and span the period January 2015 to January 2020. The dependent variable in panel A the *Number of Transactions* at each pincode-month, and the dependent variable panel B is the *Number of Investors*. Columns 1, and 3 are the the corresponding dependent variables calculated for small investors, while columns 2, and 4 are the corresponding dependent variables calculated for large investors. UPI exposure is a continuous variable that measures the regional exposure, defined as in equation 1.Post is a dummy, which takes value 1 from Q3 2016 onward. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses

Panel A: Number of Transactions

DV	Number of Transactions			
Cut-Off	Trading Value – 30,000		Trading Value –50,000	
Small Investors	Y	N	Y	N
	(1)	(2)	(3)	(4)
UPI Exposure X Post	156.271***	90.024***	175.951***	71.470***
	(8.041)	(4.983)	(9.141)	(3.875)
Pincode FE	Y	Y	Y	Y
District-Month FE	Y	Y	Y	Y
N	1,231,401	1,231,455	1,231,400	1,231,466
Adj. R^2	0.917	0.924	0.920	0.919
T-test	(2)-(1)		(4)-(3)	
	-66.247***		-104.481***	
	(9.459)		(9.928)	

Panel B: Number of Investors

DV	Number of Investors			
Cut-Off	Trading Value – 30,000		Trading Value –50,000	
Small Investors	Y	N	Y	N
	(1)	(2)	(3)	(4)
UPI Exposure X Post	19.060***	9.999***	20.076***	8.139***
	(0.917)	(0.529)	(0.978)	(0.427)
Pincode FE	Y	Y	Y	Y
District-Month FE	Y	Y	Y	Y
N	1,231,439	1,231,440	1,231,448	1,231,447
Adj. R^2	0.929	0.933	0.931	0.929
T-test	(2)-(1)		(4)-(3)	
	-9.061***		-11.937***	
	(1.059)		(1.067)	

Table 9: Mechanisms: Digital Infrastructure

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation at the regional (pincode) level. Observations are at the pincode-month level and span the period January 2015 to January 2020. The dependent variable in columns 1, and 3 is the *Number of Transactions* at each pincode-month, and the dependent variable in columns 2, and 4 is the *Number of Investors*. Columns 1, and 3 are the the corresponding dependent variables calculated for rural investors, while columns 2, and 4 are the corresponding dependent variables calculated for urban investors. UPI exposure is a continuous variable that measures the regional exposure, defined as in equation 1.Post is a dummy, which takes value 1 from Q3 2016 onward. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses

DV	Number of Transactions		Number of Investors	
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
UPI Exposure X Post	140.987***	456.202***	13.325***	45.739***
	(9.596)	(87.759)	(0.859)	(7.771)
Pincode FE	Y	Y	Y	Y
District-Month FE	Y	Y	Y	Y
N	950,779	161,140	950,715	161,260
Adj. R^2	0.934	0.969	0.928	0.975
T-test	(2)-(1)		(5)-(4)	
	315.215***		32.414***	
	(88.202)		(7.818)	

Table 10: Consequences: Return

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation at the investor level. Observations are at the pincode-month level and span the period January 2015 to January 2020. The dependent variable in columns 1(5), 2(6), 3(7), 4(8) are the excess return calculated using equation 3 for 1, 10, 15, 140 trading days. UPI exposure is a continuous variable that measures the regional exposure, defined as in equation 1. Post is a dummy, which takes value 1 from Q3 2016 onward. Investor and district-month effects are included as indicated. Investor-clustered standard errors are reported in parentheses

DV	Excess Return							
Holding Period	1 Trading Day	10 Tradingy Days	25 Trading Days	140 Trading Days	1 Trading Day	10 Tradingy Days	25 Trading Days	140 Trading Days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UPI Exposure X Post	0.000	0.000	-0.000	-0.003***	-0.000	-0.001**	-0.001**	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Small					0.004***	0.002***	-0.001	-0.015***
					(0.000)	(0.000)	(0.000)	(0.001)
UPI Exposure X Small					-0.001	-0.001	-0.000	0.005***
					(0.000)	(0.000)	(0.001)	(0.001)
Post X Small					0.000	0.001**	0.005***	-0.000
					(0.000)	(0.000)	(0.000)	(0.001)
UPI Exposure X Post X Small					0.001***	0.002***	0.001	-0.002**
					(0.000)	(0.001)	(0.001)	(0.001)
Investor FE	Y	Y	Y	Y	Y	Y	Y	Y
District-Month FE	Y	Y	Y	Y	Y	Y	Y	Y
N	108,045,406	108,016,403	107,971,591	100,480,494	108,045,406	108,016,403	107,971,591	100,480,494
Adj. R^2	0.105	0.095	0.078	0.070	0.105	0.095	0.078	0.070

Table 11: Consequences: Trading Behaviors

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation at the investor level. Observations are at the pincode-month level and span the period January 2015 to January 2020. The dependent variable in columns 1, and 4 is the *Risk Taking* measured in equation, dependent varaible in columns 2, and 5 is the *Portfolio Diversification* measured in equation 4, and dependent variable in columns 3, and 6 is *Trading Speed*. UPI exposure is a continuous variable that measures the regional exposure, defined as in equation 1. Post is a dummy, which takes value 1 from Q3 2016 onward. Investor and district-month effects are included as indicated. Investor-clustered standard errors are reported in parentheses

DV	Risk Taking (1)	Diversification (2)	Trading Speed (3)	Risk Taking (4)	Diversification (5)	Trading Speed (6)
UPI Exposure X Post	-0.003***	0.004***	0.001	-0.003***	0.005***	0.023*
	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.012)
Small				0.107***	-0.445***	-2.214***
				(0.001)	(0.001)	(0.015)
UPI Exposure X Small				0.003**	0.001	0.072***
				(0.001)	(0.001)	(0.019)
Post X Small				-0.021***	0.023***	0.339***
				(0.001)	(0.001)	(0.015)
UPI Exposure X Post X Small				0.002**	-0.003**	-0.055***
				(0.001)	(0.001)	(0.019)
Investor FE	Y	Y	Y	Y	Y	Y
District-Month FE	Y	Y	Y	Y	Y	Y
N	108,131,872	108,131,872	108,131,872	108,131,872	108,131,872	108,131,872
Adj. R^2	0.324	0.351	0.341	0.490	0.070	0.095

Appendix for

Open Payment Systems and Retail Market Access: Evidence from India's UPI

Figure A1: Stock Market Fund Transfer: Traditional Processes vs. UPI.

The infographic below presents a comparison of the transfer of funds for stock market investment using traditional processes like NEFT versus UPI. The comparison bar at the bottom highlights that UPI trades are cheaper, available 24 x 7, and take lesser time compared to traditional methods.

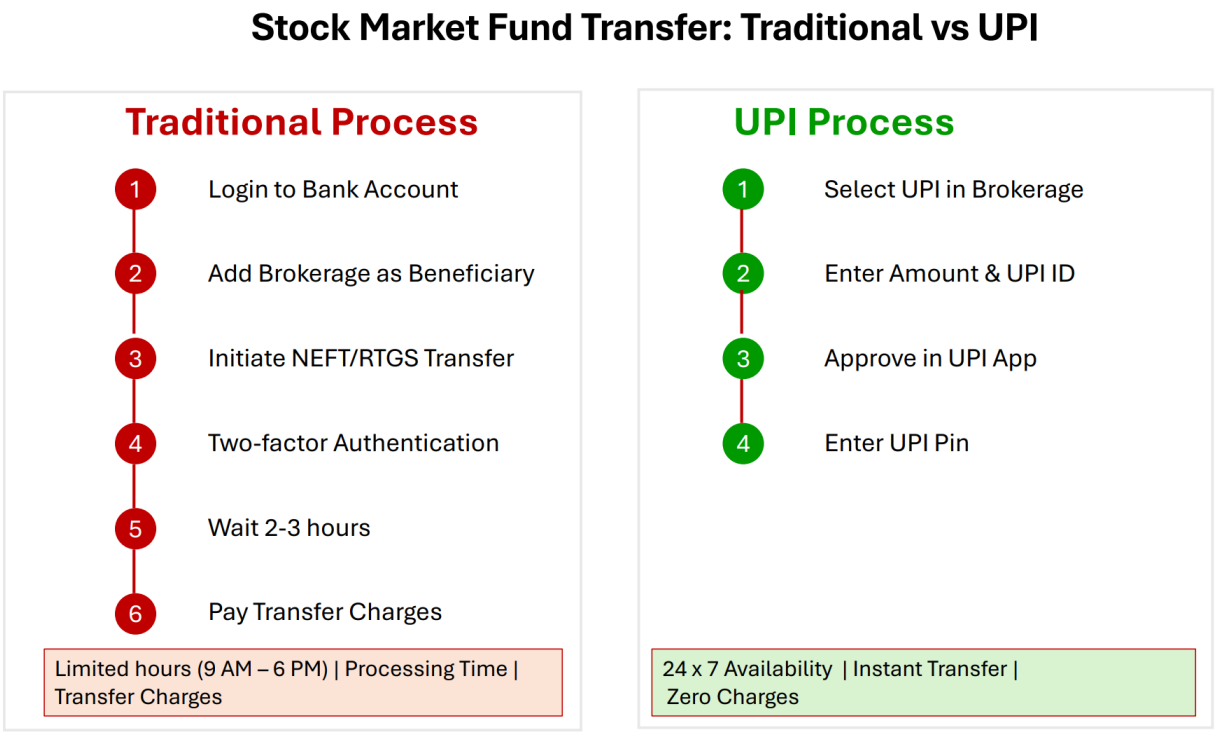
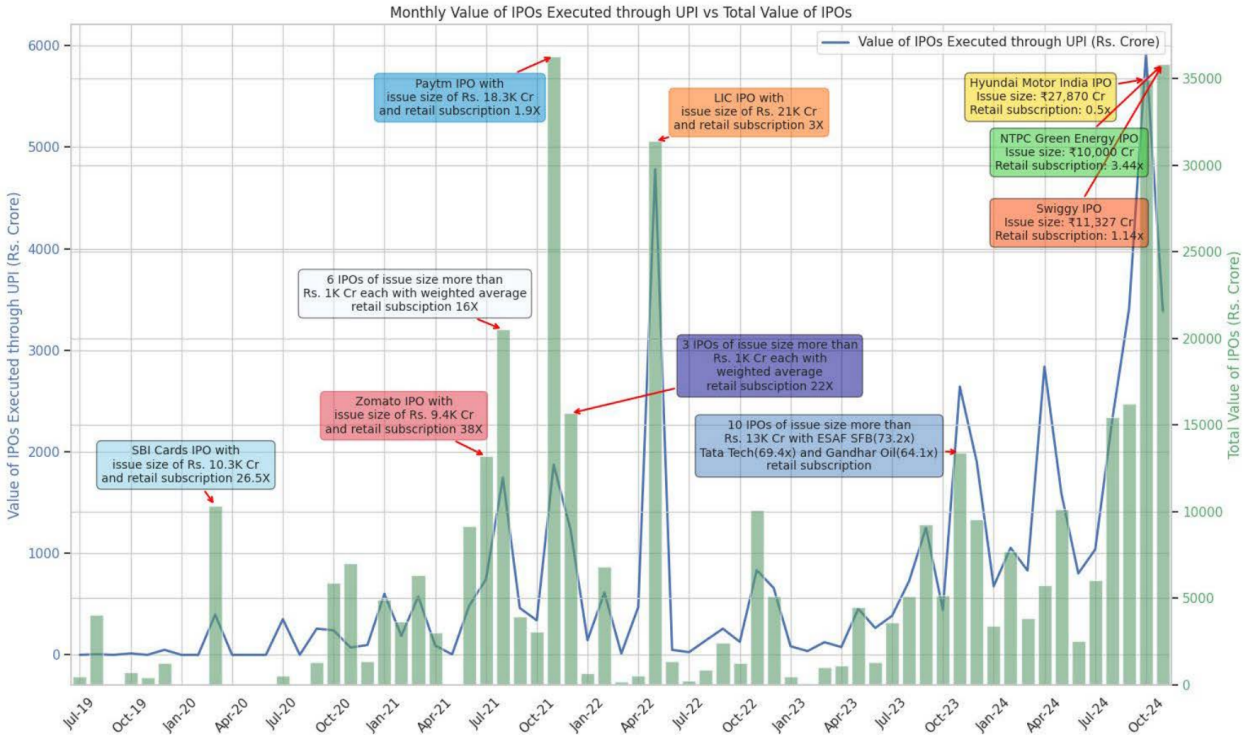


Figure A2: Trends in Increasing Usage of UPI IPO. Source: RBI Payment Systems Report

In 2019, SEBI (Securities and Exchange Board of India) introduced the One Time Mandate (OTM) functionality for IPO payments, integrated with UPI, which allowed investors to authorize payments towards an IPO using a UPI ID and PIN. This substantially streamlined the process, making it convenient for investors, and shortened the time required for public issues to be listed. The picture below, from the 2024 Reserve Bank of India (RBI) Payment Systems Report, shows that the peak transaction value for IPOs executed through UPI, each month from July 2019 to October 2024, coincides with the peak of total issue size of IPOs for that month.



Source: Zerodha Website

Table A1: Balance Test – UPI Bartik

This table compares ex-ante differences in levels and growth in economic activity and stock marker participation high-UPI Bartik and low-UPI Bartik pincodes.

Variable	(1) High UPI Bartik		(2) Low UPI Bartik		(3) Mean Difference
	N	Mean/(SE)	N	Mean/(SE)	(1)-(2)
Pincode: NSE Sample					
Economic Activity	9,306	14.875	9,307	21.007	-6.132
		(13.768)		(17.679)	
Number of Transactions	204,638	1628.943	202,416	288.837	1340.106
		(3668.848)		(1059.22)	
Number of Investors	204,638	114.776	202,416	19.525	95.251
		(266.315)		(74.212)	
Investor: NSE Sample					
Age	659,574	37.649	659,676	38.117	-0.468
		(12.849)		(13.253)	
Female	659,574	0.117	659,676	0.135	-0.018
		(0.321)		(0.343)	
Investor: Brokerage Sample					
Age	187,395	47.489	188,355	48.119	-0.630
		(11.934)		(12.126)	
Female	187,395	0.244	188,355	0.260	-0.015
		(0.430)		(0.438)	
Income: ¡5 LAC	187,395	0.448	188,355	0.438	0.011
		(0.497)		(0.496)	
Income: 5 LAC - 20 LAC	187,395	0.396	188,355	0.390	0.006
		(0.489)		(0.488)	
Income: ¿20 LAC	187,395	0.155	188,355	0.172	-0.017
		(0.362)		(0.377)	
Occupation: Public Sector	187,395	0.039	188,355	0.030	0.009
		(0.193)		(0.170)	
Occupation: Housewife	187,395	0.125	188,355	0.129	-0.004
		(0.330)		(0.335)	
Occupation: Student	187,395	0.013	188,355	0.013	0.000
		(0.113)		(0.115)	
Occupation: Business & Self-employed	187,395	0.092	188,355	0.092	0.000
		(0.289)		(0.289)	
Occupation: Private Sector	187,395	0.227	188,355	0.221	0.006
		(0.419)		(0.415)	
Occupation: Professionals	187,395	0.161	188,355	0.162	0.000
		(0.368)		(0.368)	
Occupation: Service	187,395	0.091	188,355	0.089	0.002
		(0.287)		(0.285)	
Occupation: Retired	187,395	0.076	188,355	0.083	-0.007
		(0.265)		(0.276)	
Occupation: Other	187,395	0.177	188,355	0.181	-0.004
		(0.381)		(0.385)	
Education: Post Graduate	187,395	0.092	188,355	0.095	-0.003
		(0.289)		(0.293)	
Education: Graduate	187,395	0.360	188,355	0.357	0.003
		(0.480)		(0.479)	
Education: Other	187,395	0.548	188,355	0.549	0.000
		(0.498)		(0.498)	
Credit Score: ¡ 499	187,395	0.190	188,355	0.185	0.005
		(0.392)		(0.388)	
Credit Score: 500 - 649	187,395	0.024	188,355	0.024	0.000
		(0.153)		(0.154)	
Credit Score: 650 - 749	187,395	0.044	188,355	0.042	0.002
		(0.204)		(0.200)	
Credit Score: ¿ 750	187,395	0.742	188,355	0.749	-0.006
		(0.437)		(0.434)	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Effects of UPI on Stock Market Participation: Placebo Test

This table presents the placebo test of difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation at the regional (pincode) level. Columns 1, and 2 represent the results with 100 times of randomization, while columns 3 and 4 represent the results for 500 times of randomization. Observations are at the pincode-month level and span the period January 2015 to January 2020. The dependent variable in columns 1, and 3 is the *Number of Transactions* at each pincode-month, and the dependent variable in columns 2, and 4 is the *Number of Investors*. UPI exposure is a continuous variable that measures the regional exposure, defined as in equation 1. Post is a dummy, which takes value 1 from Q3 2016 onwards. Pincode and district-month fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses

Number of Randomization	100		500	
DV	Number of Transactions	Number of Investors	Number of Transactions	Number of Investors
	(1)	(2)	(3)	(4)
UPI Exposure X Post	0.589	0.129	0.414	0.123
	(15.196)	(1.288)	(15.145)	(1.237)
Pincode FE	Y	Y	Y	Y
District-Month FE	Y	Y	Y	Y