Open Payment Infrastructure and Market Participation: The Role of Interoperability in Financial Inclusion

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ABSTRACT

How do architectural choices in payment system design affect financial market participation and structure? We examine this question by exploiting India's launch of the Unified Payments Interface (UPI), an open, interoperable payment infrastructure that enables seamless cross-platform transactions across banks and fintech applications. Unlike closed-loop systems that create institutional silos, UPI's open architecture allows users to transact across any participating platform, fundamentally altering the competitive landscape and access dynamics in financial markets. Using comprehensive data covering 19.8 million retail investors (2015-2020), we find that regions with greater exposure to early UPI-adopting banks experience substantial increases in financial market participation: 6.1% more monthly transactions and 8.6% more active investors per standard deviation of UPI exposure. Through multiple identification strategies—including natural experiments with bank holidays and telecommunications expansion, and direct comparison with State Bank of India's closed YONO platform—we demonstrate these effects stem specifically from UPI's interoperability rather than general digitization. We identify four complementary mechanisms: reduced transaction frictions enabling faster market response, lowered entry barriers for small participants, network externalities from cross-platform integration, and transformation of savings behavior. However, open architecture's democratization comes with systemic costs: small investors exhibit riskier behavior including lower diversification and negative long-term excess returns. Our findings reveal how payment infrastructure design choices create economy-wide implications for financial inclusion, market structure, and stability, providing crucial evidence for policymakers designing next-generation payment systems globally.

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1 Introduction

The architecture of payment systems – whether open and interoperable or closed and proprietary – represents one of the most consequential design choices facing financial policymakers worldwide. This fundamental decision shapes not merely how transactions are processed, but how entire financial ecosystems evolve, who can participate in markets, and how competition unfolds across financial services. Yet despite the growing global adoption of instant payment systems and the intensifying policy debate around platform interoperability, empirical evidence on how these architectural choices affect financial market structure and participation remains limited.

Traditional payment infrastructures operate as fragmented, institution-specific networks that restrict cross-platform transactions and limit market access. Users remain locked within proprietary ecosystems, unable to seamlessly move funds between different banks, fintech applications, or investment platforms without navigating complex, costly, and time-consuming processes. This fragmentation creates systematic barriers to financial market participation, particularly for smaller participants who face disproportionate friction costs. However, countries have taken markedly different architectural approaches to address these inefficiencies. Some, like China's Alipay or Kenya's M-Pesa, operate as closed-loop systems that maintain institutional silos. Others, like India's UPI, Brazil's Pix, or the EU's SEPA Instant Credit Transfer, embrace open architectures enabling true cross-platform interoperability.

This paper provides the first comprehensive empirical analysis of how open payment infrastructure affects financial market participation and structure. We exploit India's 2016 launch of the Unified Payments Interface (UPI), a uniquely powerful setting for several reasons. First, India was among the first countries to fully implement open banking, making it a pioneering case whose lessons can inform policy decisions worldwide. Second, UPI's open protocol architecture enables seamless interoperability across banks, fintech applications, and trading platforms.[1] Unlike closed systems that require users to remain within proprietary ecosystems, UPI allows any customer to transact with any merchant or platform using any participating bank account, funda-

[1]The system has been adopted widely, processing over 13 billion transactions worth 20 trillion rupees monthly by June 2024. 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.

mentally transforming the competitive dynamics of financial service delivery.

UPI's transformative impact is evident in its scale—processing over 18.6 billion transactions worth $293 billion in May 2025 alone, representing over 75% of India's retail digital payments. Its open architecture addresses multiple systemic barriers that have historically constrained financial market access. By enabling instant, zero-cost transfers between any accounts on the network, UPI eliminates settlement delays and transaction fees that disproportionately affect small participants. Its interoperable design allows investors to seamlessly move funds between banking and investment platforms without being locked into specific institutional relationships. Most importantly, UPI's open protocol enables new entrants to compete on equal footing with established players, potentially reshaping market structure and expanding access to previously underserved populations.

We present several novel findings. First, open payment infrastructure leads to increased stock market activity, both in terms of number of transactions and number of investors. Regions with greater UPI exposure experience a 6.1% increase in monthly transactions and an 8.6% rise in active investors per standard deviation of exposure. These effects represent genuine expansion of market participation rather than substitution between platforms or geographic regions. Second, we identify four specific (and complementary) mechanisms - reduced transaction frictions (validated through flash crash analysis), democratized access for small investors, network externalities in urban areas, and financialization of cash-intensive regions. 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.

Our empirical strategy leverages comprehensive data on stock trading activity from the National Stock Exchange covering over 19 million investors (2015-2020), combined with regulatory bank deposit data from the Reserve Bank of India to construct pincode-level UPI exposure measures. Following Alok et al. (2024), our main measure, *UPI Exposure* is defined as the share of total deposits held by early UPI-adopting banks in a pincode relative to total deposits across all banks. Our identification strategy leverages two key sources of variation: (1) the staggered timing of banks joining the UPI platform, and (2) geographic variation in these banks' market presence across pincodes. This dual variation helps address potential confounding effects from broader policy changes, as banks made UPI adoption decisions at the institution level rather than based on regional characteristics.[2] Using a difference-in-differences framework, we compare trading activity between high and low UPI-exposure pincodes before and after UPI implementation, controlling for pincode fixed effects and district-time fixed effects.

Identifying UPI's causal effects requires addressing the challenge that adoption correlates with digital readiness and institutional characteristics. We overcome this through four complementary identification approaches: comprehensive balance tests showing no pre-treatment differences across demographic characteristics; within-investor analysis comparing trading activity between accounts linked to early versus late adopter banks, analogous to Khwaja and Mian (2008); regional variation in bank holidays when stock markets remain open but traditional banking channels close while UPI remains functional (finding that low-UPI exposure areas demonstrate stronger relative gains during these periods); and exogenous variation in internet connectivity through Reliance Jio's 4G expansion, finding UPI's impact substantially stronger in areas gaining early access to affordable connectivity. Placebo tests using non-Jio towers confirm that the combination of affordable connectivity and UPI access, rather than general telecommunications proximity, drives increased market participation.

In addition, one concern could be that the varying local effects of demonetization are 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 could lead to greater stock market investment. Our UPI Exposure measure is not correlated with the distance to the currency chests, a key determinant of the local severity of the demonetization effects in Chodorow-Reich et al. (2020), and thus our empirical strategy relies on the variation in UPI orthogonal to the demonetization event.

As a baseline result, we first find that 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

[2]This approach works because UPI adoption requires having an account at a participating bank, and digital payment networks exhibit strong externality effects (e.g. Crouzet et al. (2023), Higgins (2022), Fafchamps et al. (2022)), creating persistent differences between areas served by early versus late adopters.

UPI in 2016. A one standard deviation higher pincode-level UPI Exposure increases the number of transactions by 68, representing a 6.1% increase relative to the mean. Correspondingly, the number of investors participating in the stock market also increases 7-fold, representing an 8.6% increase relative to the mean. The temporal dynamics also reveal a lack of pre-trends indicating that the parallel trends assumption is not violated.

Next, we provide direct evidence that interoperability, rather than general digitization, drives these outcomes. Our comparison of UPI against SBI's YONO platform – both sophisticated digital payment systems serving the same customer base – reveals that UPI's open architecture generates significantly stronger effects on market participation. This finding isolates the specific value of interoperability from broader technological advancement, consistent with growing evidence that open, interoperable infrastructure, rather than digitization alone, drives financial inclusion, adoption, and innovation by enabling cross-platform access and unbundling of financial services (e.g., Copestake et al. (2025a), Copestake et al. (2025b), and Cramer et al. (2024)).[3]

We identify four complementary mechanisms through which open architecture transforms market participation: reduced transaction frictions enabling faster response to market events, lowered barriers to entry that democratize access for small participants, network externalities that amplify adoption across the ecosystem, and financialization effects that channel savings toward market participation. First, 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. This finding demonstrates how instant settlement capabilities enable rapid market response that would be impossible under traditional banking constraints. Second, we observe a significant increase in ll transactions and greater participation from small investors [4] in pincodes with high UPI exposure. This pattern suggests that UPI's simplified infrastructure particularly benefits previously underserved investors

[3]Indeed, the temporal dynamics indicate a sharp uptick in UPI-induced participation after the RBI issued a circular strengthening interoperability in September 2017 through a multi-bank Payment-Service-Provider (PSP) model, wherein large merchants and tech players such as Gpay and Paytm could connect to the UPI system through multiple PSP banks.

[4]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.

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 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.

Fourth, we examine if UPI led to a financialization of savings through stocks. Customers need a bank account to use UPI. Thus, as UPI usage becomes more prevalent, households use their bank accounts more leading to an increase in digital transactions. We hypothesize that the ease of UPI-usage and the follow-on effects on the stock markets should be greater in regions with ex-ante high cash usage. Using the volume of cash withdrawn from ATMs per capita as a proxy for cash intensity, we indeed find that regions with ex-ante high cash-usage see a greater uptick in stock market participation in high UPI exposure pincodes.

Finally, we document both the benefits and costs of architectural openness. While UPI successfully democratizes market access, it also facilitates potentially problematic trading behaviors among less experienced participants. Small investors in high-UPI areas exhibit reduced diversification, excessive trading frequency, and negative long-term excess returns, suggesting that easier access may inadvertently encourage suboptimal decision-making.

Our findings contribute to several critical policy debates. First, they provide empirical evidence for the growing literature on payment system architecture and its implications for financial market structure. As countries worldwide implement next-generation payment infrastructure, understanding how design choices affect participation and competition becomes increasingly important for optimal policy design. Recent work has examined 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 context of UPI, a growing literature studies how digital public infrastructure affects credit access, economic activity, and platform competition. Dubey and Purnanandam (2023) provide foundational macro-level evidence that UPI-led digital payments spur economic growth and credit expansion at the district level by enhancing record-keeping and capital allocation. Their findings establish digital payments as an engine of macroeconomic development. Building on this insight, Alok et al. (2024) show that UPI adoption expands credit access by improving digital traceability, particularly benefiting previously unbanked borrowers. We extend this line of research by shifting focus from aggregate economic outcomes and credit to household-level financial behavior. Specifically, we examine how platform design – particularly openness and interoperability – shapes individual participation in financial markets. Cramer et al. (2024) further highlight the differential advantages of FinTech lenders using UPI infrastructure, especially in uncollateralized credit markets. At a structural level, Copestake et al. (2025a) shows how UPI's open architecture reshapes platform competition in India's financial sector by enabling third-party apps and modular service provision. Whereas prior work primarily examines credit outcomes, aggregate growth, or institutional responses, we focus on the extensive margin of household financial participation. Our paper thus offers a novel and complementary perspective by identifying how specific features of digital public infrastructure influence individual-level portfolio initiation and trading activity in capital markets.

Our work is also related to the emerging literature on open payment systems and its implications for market structure and consumer welfare. Recent theoretical work has examined the welfare implications of open banking frameworks (e.g., Parlour et al. (2022), He et al. (2023), and Goldstein et al. (2022)). Others such as Babina et al. (2024) provide empirical evidence on how customer data sharing through open banking affects banking relationships and credit outcomes while Alok et al. (2024) highlight how an open payment infrastructure as opposed to a closed payment infrastructure can improve financial inclusion through credit access. Many developing countries face choices about whether to build open, interoperable payment infrastructure or allow closed, platform-specific systems to dominate. Our results suggest that architectural choices have far-reaching implications for who can participate in financial markets and how those markets evolve.

Third, our evidence speaks to broader questions about financial inclusion and market development in emerging economies. Hong et al. (2020) show that FinTech adoption by households leads to higher participation in mutual-fund investments, thus, linking stock participation to digital payment transactions. Our findings suggest that while interoperability can substantially expand access and enhance competition, it may also require complementary interventions to address new risks that emerge. These findings complement the work of Gonzalez et al. (2024) who document how Pix's instant payment functionality increases banking sector liquidity demands and risk-taking incentives. Both studies suggest a broader pattern wherein payment technologies designed to reduce access barriers may inadvertently encourage excessive risk-taking – in banking systems (Gonzalez et al. (2024)) and among retail investors (our study).

The policy stakes are substantial. India's experience, where UPI has transformed not only payments but also credit access, stock market participation, and broader financial inclusion patterns, demonstrates how open architecture can reshape entire financial ecosystems. As the global financial system becomes increasingly digital, the lessons from India's open banking experiment offer crucial insights for designing payment infrastructure that promotes both access and stability.

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.[5] Its architecture comprises three distinct layers: (1) a settlement layer operated by NPCI, (2) a bank interface layer 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 A1 in the Appendix presents an infographic highlighting the ease of transfer of funds for investing via UPI versus traditional payment methods.

UPI also facilitates stock trading by allowing investors to block funds in their bank accounts

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

for trades, instead of transferring them to brokers, and then automatically deducting the amount only after the trade is executed, thereby streamlining the process and allowing funds to earn interest until needed for investment. This eliminates the need to transfer large sums to brokerage accounts upfront. Users can also track and manage block funds conveniently through their UPI app. This does not entail large upfront transfers allowing investors to save on transaction fees.

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. [6]

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.

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.[7] Its de-

[6] 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.

[7] In contrast to the government-run FedNow, RTP (Real-Time Payments) is an instant payment system launched in 2017 by The Clearing House, a private entity owned by major U.S. banks. While it also enables 24/7 real-time fund transfers, allowing transactions to settle within seconds, it operates as a closed loop system allowing for transactions

centralized, 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 (Taxpayer ID/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. Despite this commonality, UPI differs from Pix in several ways. UPI allows for the separation of the customer interface from account holding, thus enabling third-party apps like Google Pay to facilitate transactions for bank accounts. Further, Pix is integrated exclusively into banking and financial apps and transactions are completed directly from the user's banking app. In contrast, UPI has a vast ecosystem with a number of banks and third-party apps participating making UPI usage across apps seamless. Pix also charges 0.22% of all merchant transactions, whereas UPI is free. Other prominent instant payment systems include the European Union's 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.

between banks that are part of the RTP network. FedNow is designed to be more inclusive, reaching smaller banks and credit unions that may not have access to RTP.

2.2 UPI Exposure Measure

We use the pincode-level UPI exposure measure from Alok et al. (2024), which uses two key ingredients. First, 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. An individual is able to use digital payments only if their bank participates on the UPI Platform. The staggered adoption of UPI generates temporal variation in adoption of UPI by member banks. Second, there are strong network externalities in digital adoption as documented in Higgins (2022) and Crouzet et al. (2023). This generates strong spatial differences in UPI usage contingent on whether neighborhoods (pincodes) were serviced by early bank adopters.

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.[8] 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 thus 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

[8] 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.

predict greater adoption or are more technologically savvy, the pincode level variation ensures that demand and other factors 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.[9]

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 predicts UPI usage in that pincode.

We choose to rely on the UPI exposure index as our main measure since, as Alok et al. (2024) note, the measure is orthogonal to variation generated by the coincident demonetization episode that demonetized nearly 86% of the cash in circulation. We supplement this measure with a Bartik instrument, constructed as follows:

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

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.[10] 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

[9]This UPI exposure measure has also been applied in Cramer et al. (2024) to examine the effects of digital payments on shadow bank responsiveness

[10]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

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 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 investor's 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.[11]

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*

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

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%.

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.

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:

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

Where $\mathbb{I}[Buy = 1|Sell = -1]_{S,i,d}$ 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.[12] 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 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.

[12] 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.

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), stock market transactions, and 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, in both levels and growth, 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.

TABLE 2 ABOUT HERE

Appendix Table A3 shows that the Bartik exposure is also not correlated with ex-ante differences in economic activity, number of transactions, number of investors, or the age and gender profile of investors.

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

Columns 1 and 2 of Table A4 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

The role of UPI's interoperability. The vertical line in Figure 4 denotes September 2017, when the RBI issued a circular strengthening interoperability through a multi-bank Payment-Service-Provider (PSP) model, wherein a large merchant/tech player (referred to as a "third party app provider," for example, Gpay, Paytm, etc.) with access to large customer bases would be able to connect to the UPI system through multiple PSP banks. Previously, only a single bank could connect to the UPI system. as opposed to the previous limit of only one bank.[13] Figure 4 shows that effects are stronger post the multi-PSB model underscoring the role of UPI's interoperability in pushing investors into stock market participation.

A second test allows us to distinguish interoperability from general digital transactions as a channel. To this end, we compare UPI's impact against State Bank of India's proprietary digital banking platform, YONO, to distinguish the effects of UPI's open framework from bank-specific digital capabilities. The YONO test provides a unique opportunity to disentangle the effects of UPI's open framework from bank-specific digital capabilities by comparing it against SBI's propri-

[13] See NPCI circular, NPCI /UPI/OC No. 32/2017-18.

etary 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 4) and a volume-based measure (columns 3-4 in Table 4). We restrict our analysis to the period after November 2017 when both YONO and UPI are present. The analysis is at the pincode-month level and we use a specification similar to our baseline specification in Equation (5):

$$Y_{p,d,t} = \alpha_{d,t} + \beta_1 \cdot \text{UPI Exposure}_p + \beta_2 \cdot \text{Yono Exposure}_p + \varepsilon_{p,d,t} \tag{8}$$

The results in Table 4 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 payment framework plays a unique role in influencing investors to participate in the stock market.

The YONO tests restricts the analysis to only SBI and hence helps allay the concern that our baseline 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. YONO is likely to be correlated with unobservable factors determining digitization. The weak and small effects on the YONO coefficient, and the large effects documented on UPI exposure help alleviate these concerns.

TABLE 4 ABOUT HERE

Placebo tests. As further robustness, we conduct two types of placebo tests. First, we randomly reassign 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 A4, 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.

Next, we conduct a placebo test examining whether UPI adoption affects institutional investor trading. While institutional investors may benefit from UPI's infrastructure in certain operational aspects, they should not experience the same changes in market participation metrics that we observe among retail investors. Institutional trading is typically characterized by large, planned transactions executed through dedicated channels rather than the small, frequent, and occasionally opportunistic trades that define retail activity. We repeat our baseline analysis from Table 3, replacing retail investor activity with institutional investor trading as the dependent variable. Appendix Table A5 shows that consistent with our hypothesis, there is no significant relationship between UPI exposure and institutional trading patterns in the post-adoption period. The coefficients on $UPI\ Exposure \times Post$ are statistically insignificant and economically small across all specifications.

The placebo tests provides additional evidence that our results are not driven by broader market trends, regional economic developments, or other confounding factors that would likely affect all investor types.

3.1.1 Identification using within-investor variation

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 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:

$$Y_{i,b,t} = \alpha_{i,t} + \gamma_b + \beta \cdot \text{Post}_t \times \text{Early Adopter}_b + \varepsilon_{i,b,t} \tag{9}$$

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. The coefficient of interest, β captures the differential response in transactions for the same investor for the brokerage account linked to the early-adopter bank compared to the late-adopter bank.

TABLE 5 ABOUT HERE

Table 5 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, analogous to the Khwaja and Mian (2008) specification, allow us to control for all differences in transactions arising from investor-demand and investor characteristics. Thus, the investor-time fixed effects ensure that any effects driven by local economic conditions or time-varying investor characteristics are controlled for.

3.1.2 Identification using regional variation in bank holidays

One of the identification concerns is that early UPI-adopting banks might possess special characteristics (superior technology infrastructure, greater resources, more innovative practices) that could independently drive increased trading activity among their customers. If these inherent bank qualities rather than UPI itself are responsible for observed effects, it would undermine our causal interpretation of UPI's impact on market participation. To address this, we exploit regional variation in bank holidays when stock markets remain open to create a natural experiment.[14]. During these holidays, traditional banking channels are closed while UPI remains functional across all banks. The relative advantage of being with a technologically superior bank should remain evident if bank quality is driving results. We estimate the following a triple-difference specification:

$$
\begin{aligned}
Y_{p,d,D} = \alpha_{d,t} + \gamma_p + \delta_D + \theta_{s,D} + \beta_1 \cdot \text{Bank Holiday}_{p,D} + \beta_2 \cdot \textit{Post} \times \text{Bank Holiday}_{p} + \\
\beta_3 \cdot \textit{Post} \times \text{UPI Exposure}_{p} + \beta_4 \cdot \text{UPI Exposure}_{p} \times \text{Bank Holiday}_{p,D} + \\
\beta_5 \cdot \text{UPI Exposure}_{p} \times \textit{Post} \times \text{Bank Holiday}_{p,D} + \varepsilon_{p,d,D} \quad (10)
\end{aligned}
$$

Where: $Y_{p,d,D}$ represents either the number of transactions or investors in pincode p, district d, at day D; *Bank Holiday* is an indicator for bank holidays and other variables are as before. $\alpha_{d,t}$ represents district-month fixed effects; γ_p represents pincode fixed effects; δ_D represents day fixed effects; $\theta_{s,D}$ represents state-day fixed effects. The inclusion of these comprehensive fixed effects allows us to control for time-varying district-level economic conditions, pincode-level time-invariant characteristics, overall daily market movements, and state-specific daily factors.

[14] We hand collected all bank holidays in each state and the NSE holiday from 2015 and 2017, detail are shown in table A1 and A2 in the appendix.

TABLE 6 ABOUT HERE

Table 6 presents the results of this estimation. While UPI increases trading overall (the coefficient of $UPI\ Exposure \times Post$ is positive and significant), the negative triple interaction indicates that high-UPI exposure areas see a smaller incremental benefit during bank holidays compared to low-UPI areas. If superior bank characteristics were driving our results, we would expect high-UPI exposure areas to maintain or strengthen their trading advantage during bank holidays, when only digital channels remain available. Instead, we observe a convergence effect: UPI causes the gap between high and low exposure areas to narrow during bank holidays in the post-period. This suggests that UPI technology itself, rather than inherent bank characteristics, is the primary driver of increased trading activity. During bank holidays, when traditional banking is unavailable everywhere, UPI enables a stronger relative improvement in low-UPI exposure areas. This test provides further evidence that our main results identify the causal effect of UPI technology rather than general technological superiority of certain banks.

3.1.3 Identification using exogenous variation in mobile network expansion

Following our baseline difference-in-difference and Bartik instrument approaches, we further strengthen our causal identification by exploiting exogenous variation in a critical enabler of UPI usage: access to reliable, affordable internet connectivity. The entry and rapid expansion of Reliance Jio's 4G network beginning in 2016 provides an ideal setting for this analysis.

Reliance Jio dramatically transformed India's telecommunications landscape by offering high-speed data services at unprecedented price points, reducing the average cost of 1 GB of data from INR 228 in 2015 to just INR9 by 2020. Simultaneously, Jio's aggressive tower installation program decreased the average distance from pincode centroids to the nearest 4G tower from 15.1 km in 2016 to 2.1 km in 2020. Since reliable connectivity typically extends 3-6 kilometers from a tower, this expansion created significant variation in digital accessibility across pincodes.

We exploit this variation using the following triple-difference specification:

$$Y_{p,d,t} = \alpha_{d,t} + \gamma_p + \beta_1 \cdot \text{Post} \times \text{UPI Exposure}_p + \beta_2 \cdot \text{Post} \times \text{Early Jio}_p +$$
$$\beta_3 \cdot \text{Post} \times \text{UPI Exposure}_p \times \text{Early JIO}_p + \varepsilon_{p,d,t} \quad (11)$$

where $Early\ Jio_p$ identifies pincodes that had a Jio tower installed within 6 kilometers by Q1 2017. This approach allows us to test whether UPI's effect on stock market participation was amplified in areas with earlier access to affordable, high-quality internet service.

TABLE 9 ABOUT HERE

Our results in Table 9 strongly reinforce our causal interpretation. The coefficient on the triple interaction term (UPI Exposure × Post × EarlyJio) is positive and statistically significant across all specifications. This indicates that UPI's impact on market participation was substantially stronger in areas that gained early access to affordable 4G connectivity.

One potential concern with these results could be that high-UPI exposure regions closer to mobile towers may be experiencing faster economic growth. To address this, we also obtain data on the location of non-Jio mobile towers, which did not similarly lower costs or increase speed, and use these as a placebo group. Specifically, we modify the above equation by introducing two additional terms - $Post \times High\ Non - Jio_p$ and $UPIExposure \times Post \times High\ Non - Jio_p$ where $High\ Non - Jio_p$ is an indicator that takes the value one for pincodes that were within 6 km of a non-Jio tower as of 2017 Q2. The triple difference, Non-Jio X UPI Exposure X Post captures the differential effect of UPI exposure on market participation in areas ex-ante covered by non-Jio towers relative to other areas. Results in columns 3–4 show that the coefficient estimate on this triple interaction is much more muted and the differential effect of Jio is at least two times that of non-Jio coverage.

By combining this triple-difference approach with our previous identification strategies, we provide robust evidence that the expansion of open payment infrastructure through UPI causally increased retail stock market participation.

3.2 Heterogeneity

In this section, we examine whether the stimulating effects of UPI on stock market participation differ across various demographic groups, brokerage types, and trading channels. Specifically, we leverage information on investors' gender, age group, [15], whether they trade through FinTech brokerages, and whether the trading activities are conducted at a physical location or via the internet. For each subgroup among the gender, age group, and fintech brokerage, we calculate two key measures: the *Number of Transactions* and the *Number of Investors*. For transactions that are conducted either via physical location or internet, we are only able to calculate the *Number of Transactions* one investor could trade on multiple channels and we don't have information on the count of investors for each channel. This approach allows us to assess whether UPI's impact is uniform or whether it varies systematically across different segments of the investor population.

TABLE 7 ABOUT HERE

The estimation results for gender, age group, and fintech brokerage are reported in Table 7. Overall, UPI exposure has a statistically significant positive effect on transaction numbers across most groups. When comparing the coefficients to the sample means (at the bottom row), we can see that by age, young investors see highest impact (52.6% increase =66.8/126.9) followed by middle-aged (20.5% increase =123.6/604.2). By gender, female investors see higher impacts (35.8% increase) than males (19.0% increase) and fin-tech users see much bigger increase (71.6% increase) than non-fintech (5.1% increase).

When we look at number of investors, we see that UPI exposure has a statistically significant positive effect on the number of investors across all demographic groups When comparing the coefficients to the sample means, these results are largely consistent with the transaction volume findings: Young investors show the highest proportional increase in both transactions and investor numbers, followed by middle-aged investors. While females show a smaller absolute increase, their proportional increase (42.2%) exceeds males (26.0%), consistent with the transaction findings. FinTech platforms show the highest proportional increase in investor numbers (71.7%), consistent

[15] We categorize investors into three age groups based on the following criteria: Young (18–30 years old), Middle-aged (30–55 years old), and Mature (above 55 years old).

with the transaction data (71.6%).

In Table 8, we explore whether the impact of UPI differs by trading channel. In Columns 1 and 2, we estimate the effect of UPI exposure on the number of transactions conducted at physical locations versus those conducted through internet-based platforms. We find a statistically significant negative effect on physical transactions, with an average reduction of 87.03 transactions, while internet-based transactions increase by 140.31 on average following UPI exposure. Relative to the sample means, this translates to a 26.4% decline for physical transactions and a 28.4% increase for internet-based transactions. These results suggest that UPI not only expands participation but also shifts trading activity toward digital channels, reinforcing the idea that UPI facilitates more convenient and accessible forms of market engagement.

TABLE 8 ABOUT HERE

Together, these results suggest that UPI has democratized investment access, with particularly strong effects for young investors, women, and users of FinTech platforms. The largest proportional impact is on FinTech platforms, suggesting UPI integration works especially well with digital-first financial services.

3.3 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.[16] 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.[17] 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 trans-

[16]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.

[17]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.

actions. Furthermore, users can link multiple bank accounts to a single UPI app, allowing them 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.

3.3.1 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. While UPI's role in investor responsiveness to market opportunities is obvious, it can be important at the time of selling too as investors might want to transfer funds out of their trading accounts.

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[18] 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

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

and its designation as a global health crisis by the World Health Organization. [19]

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

$$Y_{i,h} = \delta_i + \gamma_h + \beta \cdot \text{UPI Exposure}_i \times \text{Post Crash}_h + +\varepsilon_{i,h} \tag{12}$$

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 10 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 UPI's 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

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

enhancing market efficiency and resilience, particularly in the context of emerging economies with rapidly evolving financial infrastructures.

3.3.2 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:

$$Small\_Trading_{p,d,p,t} = \alpha_{d,t} + \gamma_p + \beta \cdot \text{Post} \times \text{UPI Exposure}_p + \varepsilon_{p,d,p,t} \tag{13}$$

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 11 ABOUT HERE

The results highlight that UPI exposure significantly reduces entry barriers for small investors, facilitating increased participation in stock market activity. Table 11 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.

3.3.3 Digital Infrastructure

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.[20]

TABLE 12 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,

[20] 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.

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.

3.3.4 Financialization of Savings

In order to use UPI, customers need a bank account. As the ease of transacting digitally improved, UPI potentially increased the amount of funds in the formal banking system. Given this greater financialization of savings, we expect that stock market participation should be greater in areas with ex-ante greater cash usage

We examine the heterogeneity with ex-ante cash usage using the following triple-difference specification:

$$\begin{aligned} Y_{p,d,t} = \alpha_{d,t} + \gamma_p + \beta_1 \cdot \text{Post} \times \text{UPI Exposure}_p + \beta_2 \cdot \text{Post} \times \mathbb{1}_{Top\ Tercile\, p} + \\ \beta_3 \cdot \text{Post} \times \text{UPI Exposure}_p \times \mathbb{1}_{Top\ Tercile\, p} + \varepsilon_{p,d,t} \end{aligned} \tag{14}$$

We proxy for cash-intensity using ATM withdrawals in the ex-ante period before UPI. $\mathbb{1}_{Top\ Tercile}$ identifies pincodes that are in the top tercile of ATM withdrawals per capita as of March 2016 based on data from RBI. This specification allows us to test whether UPI's effect on stock market participation is greater in areas where cash-usage was higher pre-UPI.

TABLE 13 ABOUT HERE

Table 13 presents the results. Column 1 suggests that indeed, pincodes with high ex-ante cash usage see number of transactions increase by 310 transactions (coefficient on $\mathbb{1}_{Top\ Tercile} \times$ UPI Exposure $\times\ \mathbb{1}_{Post}$) on average relative to the baseline effect of 63 transactions on the remaining two bottom terciles (UPI Exposure $\times\ \mathbb{1}_{Post}$). Similarly column 2 suggests a larger 6.9x (=36.6/5.3) increase in the number of investors for pincodes in the top tercile of cash usage. This result underscores how UPI increased the formalization of savings, which households then used to invest in financial assets such as stocks.

Overall, our empirical tests identify four 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, leverages existing digital payment networks to build trust in electronic financial services and improves financialization of savings through stock market participation.

4 Consequences of UPI-Induced Retail Participation

In this section, we investigate whether UPI adoption produces measurable effects on investor outcomes through two key dimensions: investment performance (excess returns) and trading behavior patterns. We focus particularly on how these effects might differ between small and regular investors, given our earlier findings about UPI's democratizing effects.

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. Specifically, we estimate the following equation:

$$Y_{i,p,d,t} = \kappa_i + \lambda_{d,t} + \beta \cdot \text{Post} \times \text{UPI Exposure}_p + \varepsilon_{i,d,t} \tag{15}$$

To isolate differential effects for small investors, we then employ a triple interaction model by incorporating an indicator variable for small investors into the DiD model.

$$\begin{aligned} Y_{i,p,d,t} = \kappa_i + \lambda_{d,t} + \beta_0 \cdot \text{Post} \times \text{UPI Exposure}_p + \beta_1 \cdot \text{Small} + \\ \beta_2 \cdot \text{Small} \times \text{UPI Exposure}_p + \beta_3 \cdot \text{Post} \times \text{Small} + \\ \beta_4 \cdot \text{Post} \times \text{UPI Exposure}_p \times \text{Small} + \varepsilon_{i,p,d,t} \end{aligned} \tag{16}$$

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.

Table 14 displays the results for excess return and Table 15 shows the results for trading behaviors. Our analysis of excess returns reveals a striking temporal pattern (Table 14). For the broader investor population, the coefficients on $UPI\ Exposure \times Post$ for shorter holding periods (1, 10, and 25 trading days) are small and not statistically significant. However, the 140-day horizon reveals a significant negative effect, suggesting that while UPI doesn't immediately alter investment outcomes, it may degrade long-term performance, potentially through encouraging excessive trading or less disciplined investment strategies.

TABLE 14 ABOUT HERE

Small investors demonstrate a markedly different pattern. The triple interaction reveals significant positive effects on excess returns over short and medium horizons (1 and 10 trading days), suggesting initial benefits from UPI adoption. However, these advantages dissipate and even reverse over longer horizons (25 and 140 trading days), with coefficients becoming insignificant or significantly negative. This trajectory suggests that while small investors initially benefit from UPI adoption, their long-term performance deteriorates, potentially due to over-trading or suboptimal investment choices.

Table 15 further examines the impact of UPI adoption on trading behaviors, including risk-taking, diversification, and trading speed. For the general investor population, UPI exposure significantly reduces risk-taking and enhances portfolio diversification, both positive developments suggesting more prudent investment strategies. Trading speed remains largely unchanged, indicating that while UPI alters what investors trade, it doesn't necessarily accelerate how frequently they trade.

TABLE 15 ABOUT HERE

Small investors, however, show distinctive behavioral responses to UPI adoption. The triple interaction reveals that they trade more frequently (increased speed), hold less diversified portfolios, and don't experience the same risk-reduction benefits as other investors. These findings suggest that UPI creates a behavioral trade-off for small investors: it provides easier market access but simultaneously promotes potentially problematic trading patterns characterized by concentrated positions, more frequent transactions, and relatively higher risk-taking. These behavioral changes help explain the longer-term underperformance we found earlier as the negative consequences of less diversified, higher-frequency trading manifest over time.

5 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 6.1% increase in monthly transactions and a 8.6% increase in active investors relative to low-exposure regions, highlighting the substantial economic impact of reducing payment frictions.

Our analysis identifies four 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. Fourth, UPI enables financialization of savings and the UPI induced stock market participation is more pronounced in neighborhoods with ex-ante high-cash usage.

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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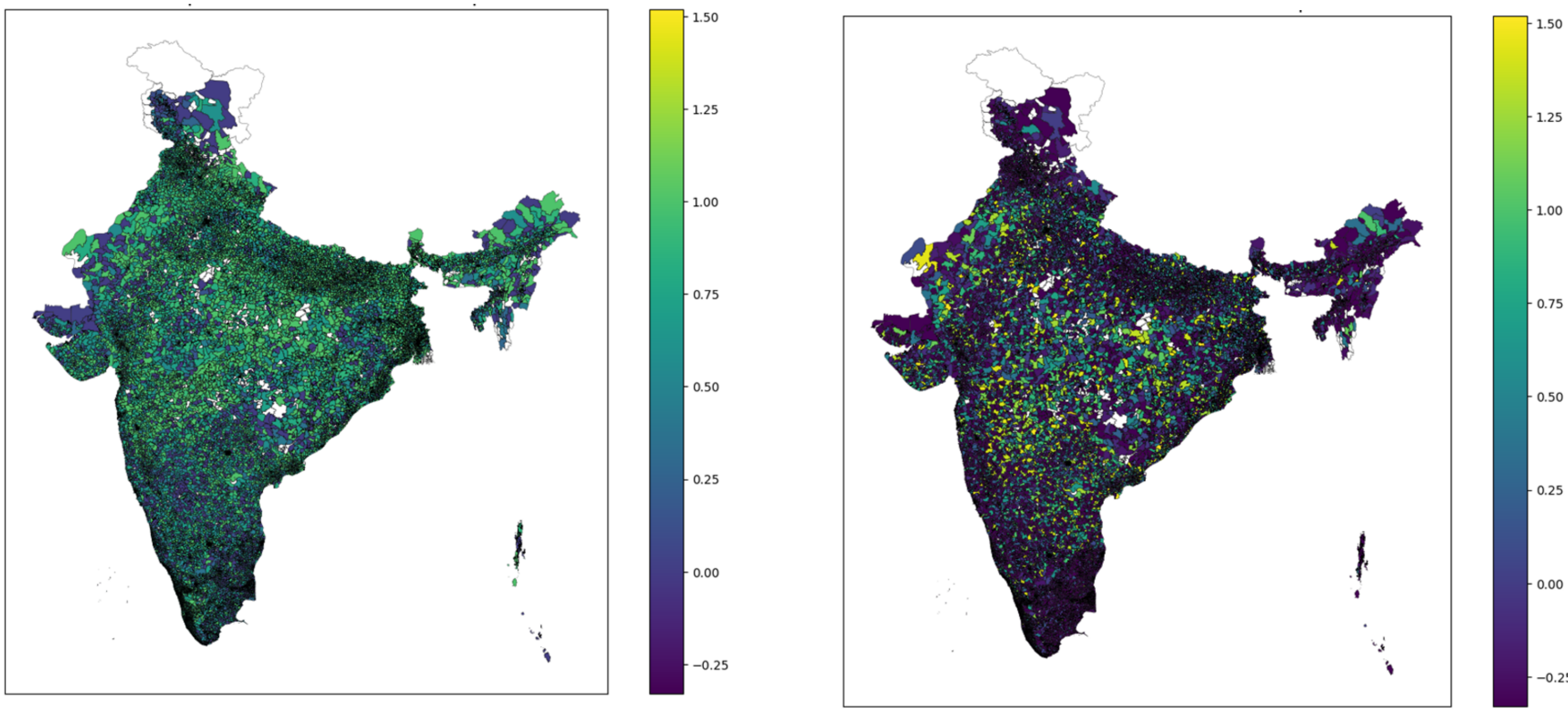
Figure 1
Geographic Variation in UPI Exposure

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.



(A) UPI Exposure India Pincode Heatmap

(B) UPI Bartik India Pincode Heatmap

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 for the period Q1 2015 to Q1 2020.

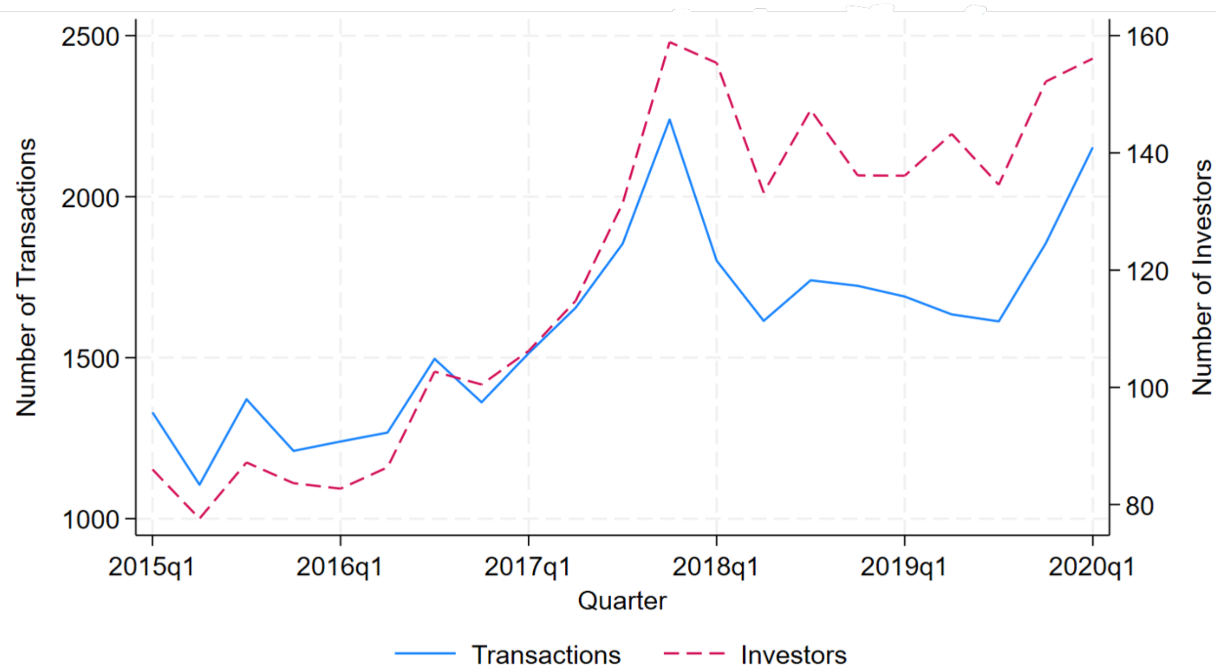
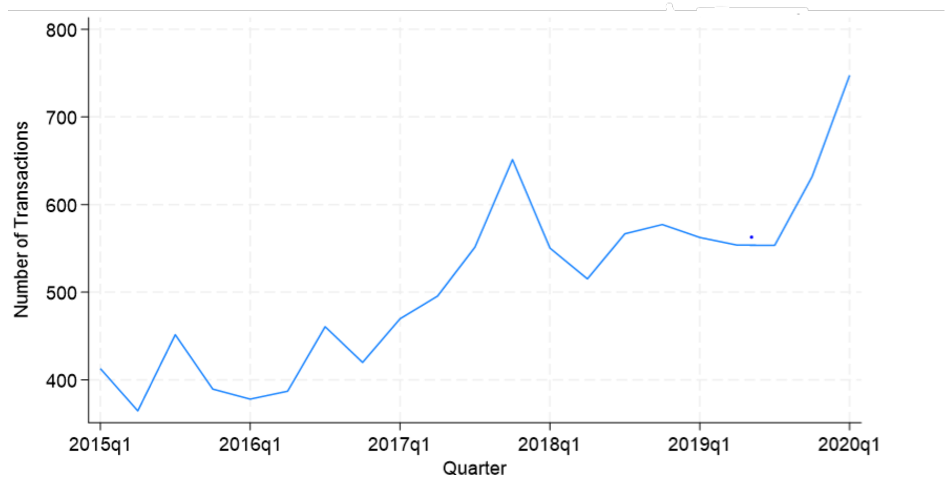
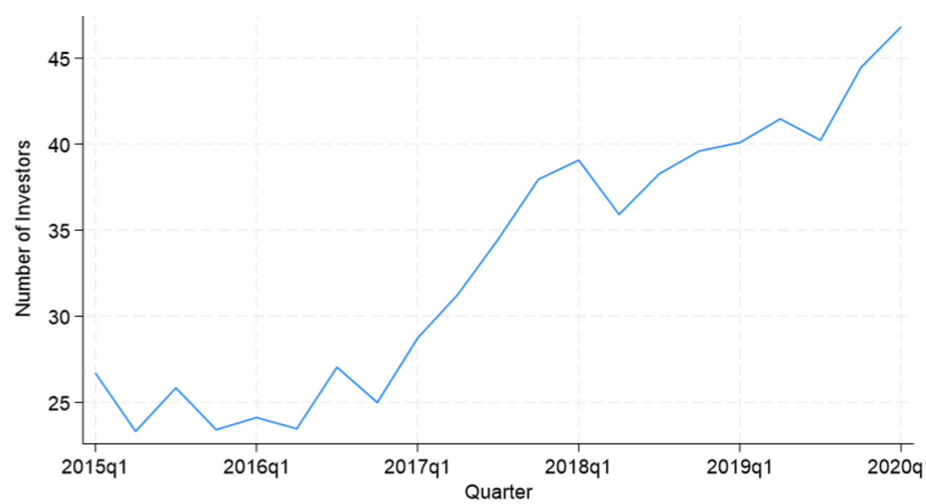


Figure 3
UPI and Stock Market Participation

This figure illustrates the difference in the average number of retail transactions (left) and retail investors (right) between high- and low-UPI exposure pincodes. Trading data is at the monthly frequency from first quarter of 2015 to first quarter of 2020 and aggregated to the pincode level separately low low and high exposure areas. The difference between the two groups (high-low) is plotted below. High (low) refers to pincodes with above (below) the median values of UPI exposure.



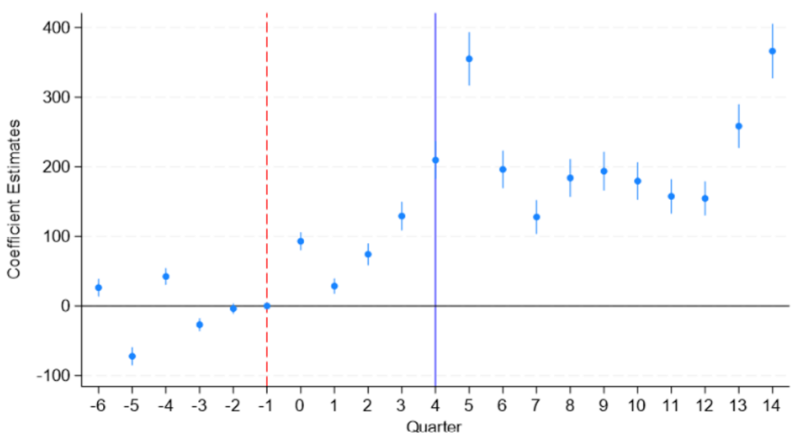
(A) Difference Between Number of Transactions (High Low)



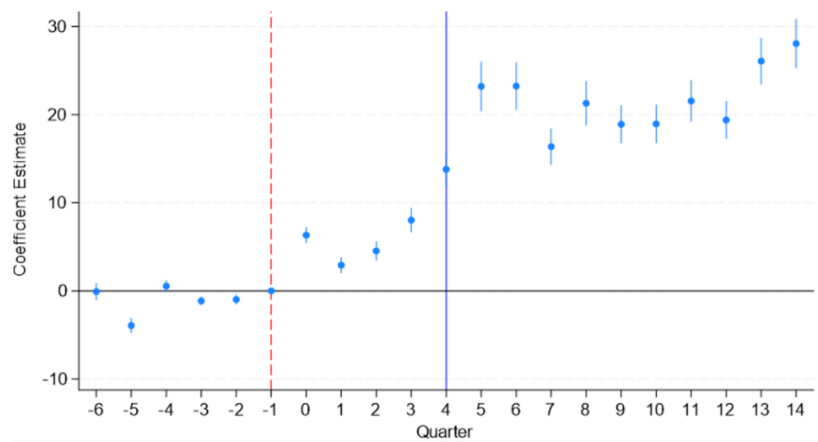
(B) Difference Between Number of Investors (High Low)

Figure 4
Dynamic Effects of UPI on Stock Market Participation

This figure presents treatment dynamics 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, a circular released by the Reserve Bank of India that strengthened the open banking system.



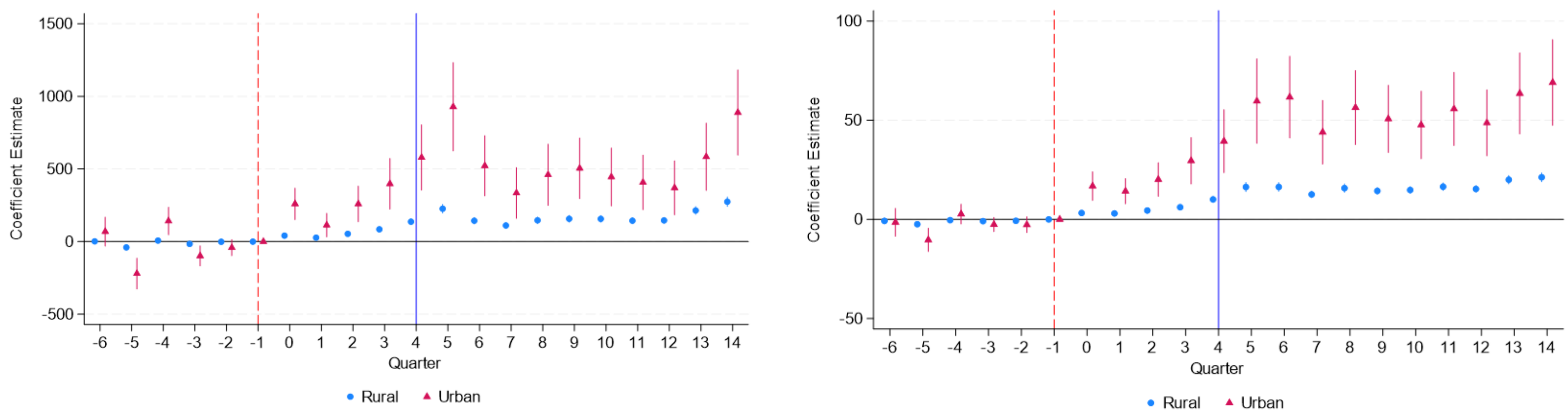
(A) Number of Transactions



(B) Number of Investors

Figure 5
Dynamic Effects of UPI on Stock Market Participation – Rural vs Urban Pincodes

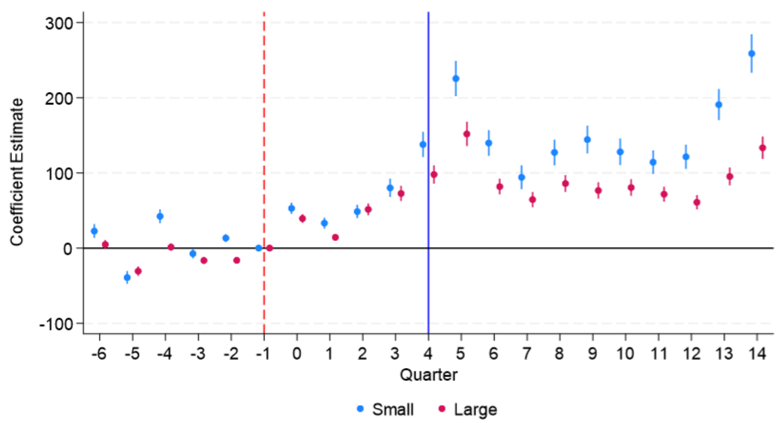
This figure presents treatment dynamics using the specification in equation 5 for the number of retail transactions (left) and the number of retail investors (right) in rural (blue dots) and urban (red triangles) areas. The underlying data, aggregated at the pincode level, is at a quarterly frequency 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).



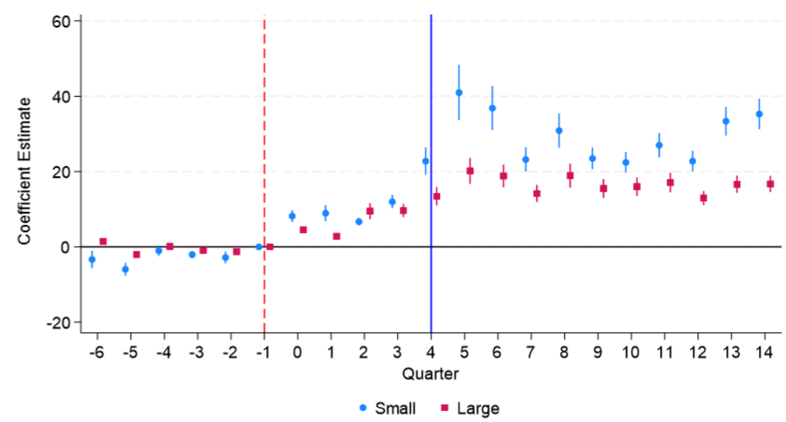
(A) Number of Transactions **(B) Number of Investors**

Figure 6
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. An investor is classified as 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).



(A) Number of Transactions



(B) Number of Investors

Table 1
Summary Statistics

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

This table reports the summary statistics for key variables in our analysis. The table summarizes mean values of the key variables for high and low UPI Exposure and the difference between them. The variables included are the pincode-month level stock market participation, namely, *Number of Transactions* and *Number of Investors*) and investor trading behavior measures (*buy and hold returns (BHR)*, *Risk Taking*, *Portfolio Diversification*, and *Trading Speed*) at the investor level). The data is from January 2015 to January 2020.

Table 2
Balance Test by UPI Exposure

Variable	(1) High UPI Exposure N	(1) High UPI Exposure Mean/(SE)	(2) Low UPI Exposure N	(2) Low UPI Exposure Mean/(SE)	(3) Mean Difference (1)-(2)
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)	
Growth in Number of Transactions	204,754	0.230	204,732	0.260	-0.03
		(2.009)		(2.429)	
Growth in Number of Investors	204,754	0.047	204,732	0.048	-0.001
		(0.418)		(0.440)	
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)	

This table compares ex-ante differences across high-exposure and low-exposure pincodes in the following variables for the period of Jauuary 2015 to June 2016: Levels of economic activity as proxied by night-light intensity; Stock market activity as proxied by the Number of Transactions, Number of Investors, Growth in Number of Transactions, and Growth in Number of Investors.

Table 3
UPI and Stock Market Participation

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

This table presents the difference-in-difference (DiD) and Bartik instrument estimates for the impact of UPI exposure on stock market participation. Observations are at the pincode-month level for the period January 2015 to January 2020. The dependent variable in columns 1 and 3 is the *Number of Transactions* 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, as defined in equation 1. UPI Bartik is calculated as the product of the national UPI over time and the pincode-level UPI-GDP measured as September 2017. The variable *Post* is a dummy variable equal to 1 from Q3 2016 onward. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 4
Comparing Open vs. Closed Payment Systems: UPI Expsoure and SBI's YONO

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

This table shows the comparison of UPI exposure (an open payment system) with YONO, a digital banking platform (a closed payment system) launched by the State Bank of India (SBI) in 2017. The sample is restricted to accounts linked to SBI. YONO exposure is value (columns 1-2) or volume (columns 3-4) of YONO transactions as of Q4 2018. Observations are at the pincode-month level. The dependent variables are *Number of Transactions* (columns 1 amd 3) and *Number of Investors* (columns 2 and 4). Columns 1–2 (3–4) use YONO calculated in value (volume) terms. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. All regressions include district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 5
UPI and Stock Market Participation: Within-Investor Variation

Sample	Investor with two or more brokers during entire sample period	Investor with two or more brokers in each month	
DV	Number of Transactions		
	(1)	(2)	(3)
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

This table presents the difference-in-difference (DiD) estimates for the impact of UPI adoption on stock market participation. Observations are at the investor level for the period January 2015 to January 2020. The dependent variable is *Number of Transactions* for each investor level. Column 1 is restricted to the sample of investors with two or more brokerage accounts during the sample period. Columns 2 and 3 is further restricted to investors with two or more brokerage accounts in each month. Early UPI Enabled Brokerage is a dummy variable that equals 1 if the bank associated with the brokerage account is an early UPI adopter. The variable *Post* is a dummy variable equal to 1 from Q3 2016 and later. Investor, district-month, and broker fixed effects are included in columns 1 and 2; and district-month, broker, and investor-month fixed effects are included in column 3. Standard errors are clustered at the investor level and reported in parentheses.

Table 6
UPI and Stock Market Participation: Bank Holiday

	Number of Transactions (1)	Number of Investors (2)	Number of Transactions (3)	Number of Investors (4)
Bank Holiday	-0.679***	-0.485***		
	(0.151)	(0.044)		
Post X UPI Exposure	10.109***	3.324***	10.097***	3.331***
	(0.673)	(0.205)	(0.677)	(0.208)
Bank Holiday X UPI Exposure	-2.667***	-0.917***	-2.953***	-0.936***
	(0.240)	(0.066)	(0.257)	(0.072)
Post X Bank Holiday	1.471***	0.535***		
	(0.350)	(0.103)		
Post X Bank Holiday X UPI Exposure	-0.903*	-0.600***	-0.890	-0.644***
	(0.500)	(0.143)	(0.555)	(0.159)
Pincode FE	Y	Y	Y	Y
Day FE	Y	Y		
State-Day FE			Y	Y
District-Month FE	Y	Y	Y	Y
N	2058065	2058068	2058019	2058022
Adj. R2	0.952	0.962	0.953	0.963

This table presents the triple difference-in-difference (DDD) estimates for the impact of UPI adoption on stock market participation at the pincocde level. The unit of observation is the pincode-day, covering the bank holiday January 2015 to December 2019. The dependent variable in columns 1 and 3 is the *Number of Transactions* for each pincode-day, and the dependent variable in columns 2 and 4 is the *Number of Investors*. *Bank Holiday* is an indicator for bank holidays, but when the Nationalk Stock Exchange (NSE) is open. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 onward. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 7
UPI and Stock Market Participation: Heterogeneity

Panel A: Number of Transactions

DV	Number of Transactions						
	Young	Middle Age	Mature	Female	Male	FinTech	Non-FinTech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UPI Exposure X Post	66.799***	123.613***	-0.494	21.756***	167.003***	136.717***	45.820***
	(2.955)	(6.658)	(3.025)	(1.321)	(9.243)	(5.709)	(7.018)
Pincode FE	Y	Y	Y	Y	Y	Y	Y
District-Quarter FE	Y	Y	Y	Y	Y	Y	Y
N	1121302	1121362	1121328	1121330	1121365	1121342	1121378
Adj-R sq	0.813	0.955	0.963	0.846	0.962	0.742	0.970
Sample Mean	126.927	604.184	352.469	60.809	878.725	190.894	897.110

Panel B: Number of Investors

DV	Number of Transactions						
	Young	Middle Age	Mature	Female	Male	FinTech	Non-FinTech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UPI Exposure X Post	6.492***	11.150***	2.041***	2.109***	16.799***	8.305***	12.065***
	(0.285)	(0.577)	(0.181)	(0.116)	(0.826)	(0.341)	(0.752)
Pincode FE	Y	Y	Y	Y	Y	Y	Y
District-Quarter FE	Y	Y	Y	Y	Y	Y	Y
N	1121304	1121403	1121379	1121400	1121392	1121325	1121409
Adj-R sq	0.835	0.965	0.981	0.904	0.961	0.763	0.975
Sample Mean	11.697	46.692	21.602	4.994	64.638	11.583	69.963

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation. Observations are at the pincode-month level for the period January 2015 to January 2020. The dependent variable in panel A is the *Number of Transactions* in each pincode-month, and the dependent variable in panel B is the *Number of Investors*. Columns 1 and 3 are the corresponding dependent variables calculated for each age group, while columns 4 and 5 are the corresponding dependent variables calculated for gender group, while columns 6 and 7 are the corresponding variables calculated for FinTech and Non-FinTech brokers. UPI exposure is a continuous variable that measures the pincode-level exposure, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 and later. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 8
UPI and Stock Market Participation: Physical Trading vs Internet Trading

DV	Number of Transactions	
	Physical	Internet-based
	(1)	(2)
UPI Exposure X Post	-87.031***	140.306***
	(5.704)	(6.054)
Pincode FE	Y	Y
District-Quarter FE	Y	Y
N	1091723	1102910
Adj-R sq	0.862	0.771
Sample Mean	329.9023	494.150

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation. Observations are at the pincode-month level for the period January 2015 to January 2020. The dependent variable in all columns is the *Number of Transactions*. Column 1 is the corresponding dependent variable calculated for physical trading, while column 2 is the corresponding dependent variable calculated for internet-based trading. UPI exposure is a continuous variable that measures the pincode-level exposure, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 and later. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 9
UPI and Stock Market Participation: Mobile Network Expansion

	Number of Transactions (1)	Number of Investors (2)	Number of Transactions (3)	Number of Investors (4)
UPI Exposure X Post	105.546***	10.344***	50.069**	4.162**
	(12.088)	(1.116)	(22.912)	(2.086)
Post X Early JIO	127.663***	12.777***	116.467***	11.698***
	(14.292)	(1.242)	(14.139)	(1.238)
UPI Exposure X Post X Early JIO	154.594***	16.907***	148.936***	16.225***
	(20.446)	(1.808)	(20.174)	(1.798)
Post X High No-JIO			95.509***	9.410***
			(17.910)	(1.679)
UPI Exposure X Post X High No-JIO			63.459***	7.148***
			(23.673)	(2.175)
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	0.964	0.965

This table presents the triple difference-in-difference (DDD) estimates for the impact of UPI adoption on stock market participation at the pincode level. The unit of observation is the pincode-month, covering the period from 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*. *Early JIO* identifies pincodes that had a JIO tower installed within 6 kilometers by Q1 2017. *High No-JIO* is an indicator that takes the value one for pincodes that were within 6 km of a non-JIO tower as of 2017 Q2. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 onward. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 10
Mechanism: Reduction in Transaction Costs

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

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation during a stock market crash. Observations are at the investor-hour level and span a 12-trading-hour-window before and after the two stock market crashes in 2019 and 2020. The dependent variable in columns 1, 3, and 5 is the *Number of Transactions* by 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 the two market crashes, while columns 3 (5), and 4 (6) are the corresponding dependent variables for the event in 2019 (and 2020) respectively. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. *Post Crash* is a dummy variable, which takes value 1 for the 12-hours post market crash. All regressions include investor and hour effects as indicated. Standard errors are clustered at the investor level and reported in parentheses.

Table 11
Mechanism: Lower Entry Barriers

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)	

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation. Observations are at the pincode-month level for the period January 2015 to January 2020. The dependent variable in panel A is the *Number of Transactions* in each pincode-month, and the dependent variable in 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 pincode-level exposure, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 and later. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 12
Mechanism: Digital Infrastructure

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)	

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation. Observation are at the pincode-month for the period January 2015 to January 2020. The dependent variable in columns 1 and 3 is the *Number of Transactions* in each pincode-month, and the dependent variable in columns 2 and 4 is the *Number of Investors*. Columns 1 and 3 (columns 2 and 4) are the corresponding dependent variables for rural (urban) investors. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. *Post* is a dummy variable equal to 1 from Q3 2016 and later. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 13
Mechanism: Financialization of Savings

DV	Number of Transactions (1)	Number of Investors (2)
$\mathbb{1}_{Top\ Tercile} \times$ UPI Exposure $\times \mathbb{1}_{Post}$	309.773***	36.636***
	(36.852)	(3.309)
$\mathbb{1}_{Top\ Tercile} \times \mathbb{1}_{Post}$	220.990***	23.613***
	(25.100)	(2.217)
UPI Exposure $\times \mathbb{1}_{Post}$	63.057***	5.317***
	(13.594)	(1.224)
R^2	0.967	0.968
Disym FE	Y	Y
Pin FE	Y	Y
N	981336	981377

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation. Observations are at the pincode-month for the period January 2015 to January 2020. The dependent variable in column 1 is the *Number of Transactions* and the dependent variable in column 2 is the *Number of Investors*. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. *Post* is a dummy variable equal to 1 Q3 2016 and later. $\mathbb{1}_{Top\ Tercile}$ is an indicator equal to one for pincodes with in the top tercile of the amount of ATM withdrawals per capita as of March 2016. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table 14
Consequences: Return

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 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

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

Table 15
Consequences: Trading Behavior

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

This table presents the difference-in-difference (DiD) estimates for the impact of UPI exposure on stock market participation at the investor level. The unit of observation is the pincode-month, covering the period from January 2015 to January 2020. The dependent variable is *Risk Taking* in columns 1 and 4, *Portfolio Diversification* in columns 2 and 5, and *Trading Speed* in columns 3 and 6. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 onward. All regressions include investor and district-month fixed effects, as indicated. Standard errors are clustered at the investor level and reported in parentheses.

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

Online Appendix

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.

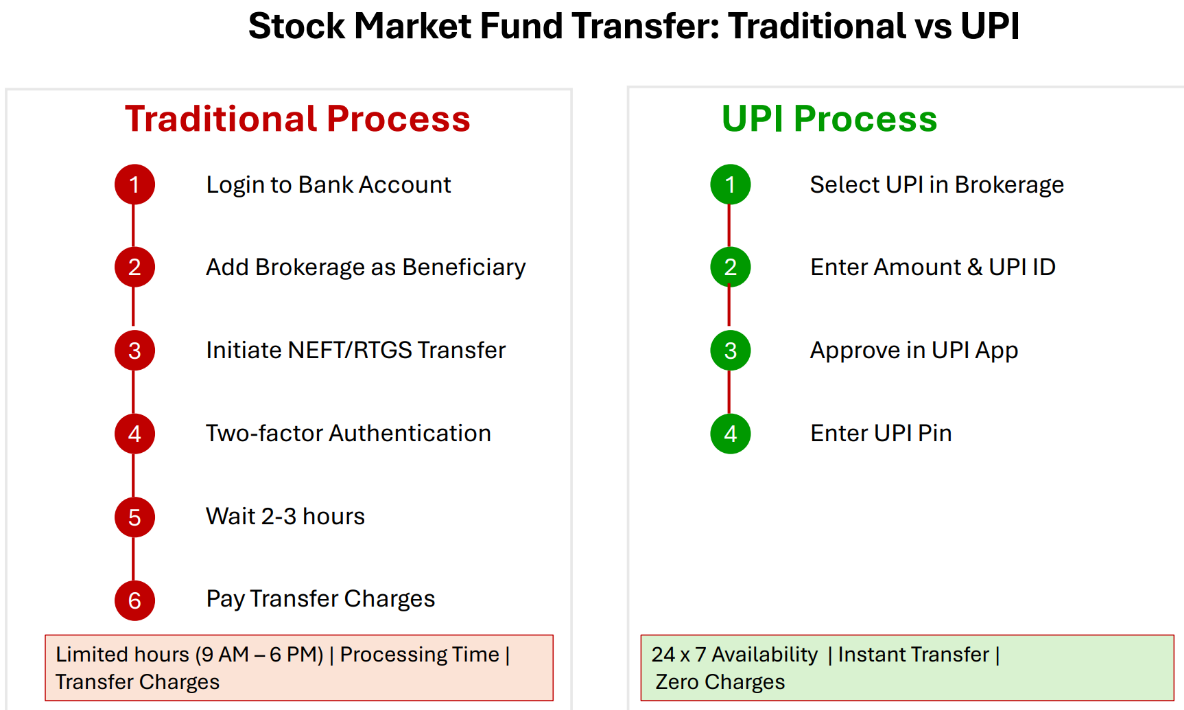
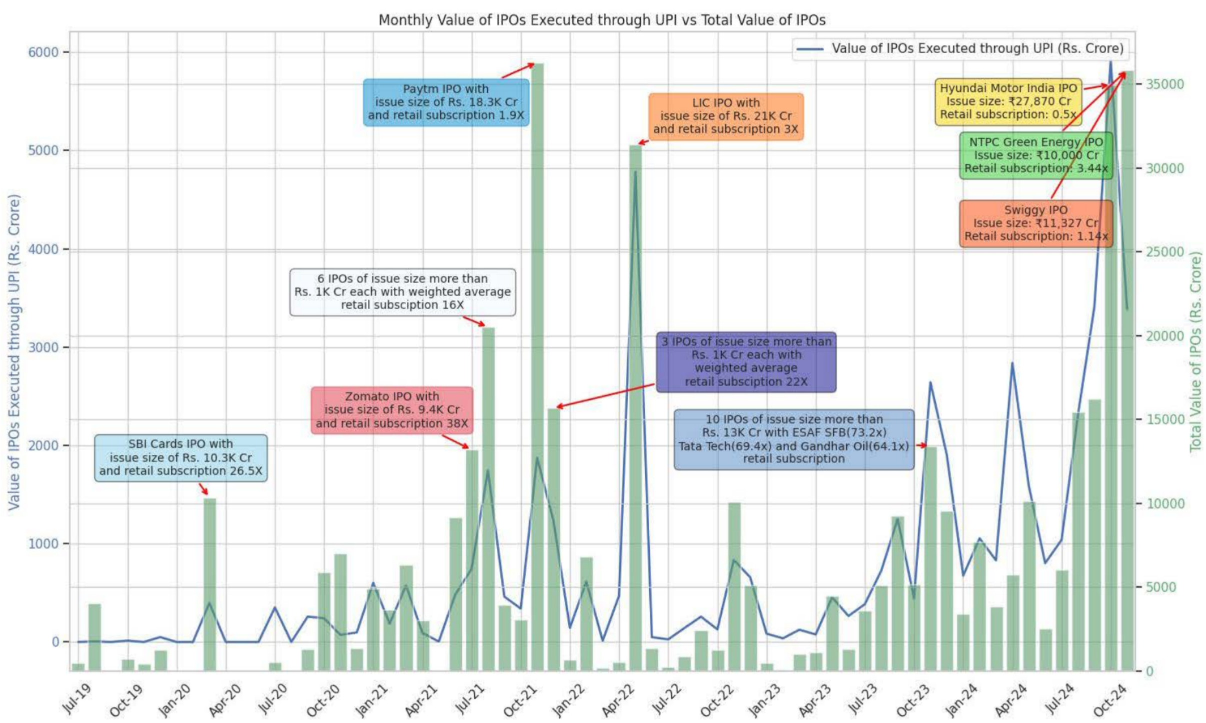


Figure A2
Trends in Increasing Usage of UPI IPO. Source: RBI Payment Systems Report

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
Bank Holidays in Each State

State	Date
Andaman & Nicobar Islands	2015-01-15, 2015-01-26, 2015-03-06, 2015-04-03, 2015-07-18, 2015-08-15, 2015-08-28, 2015-09-05, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-25, 2015-12-24, 2015-12-25
Andhra Pradesh	2015-01-04, 2015-01-15, 2015-01-26, 2015-02-17, 2015-03-05, 2015-03-21, 2015-04-03, 2015-04-14, 2015-07-18, 2015-08-15, 2015-09-17, 2015-09-24, 2015-10-02, 2015-10-20, 2015-10-22, 2015-12-24, 2015-12-25, 2016-01-15, 2016-01-26, 2016-03-07, 2016-03-23, 2016-04-08, 2016-04-14, 2016-04-15, 2016-07-06, 2016-08-15, 2016-09-05, 2016-10-02, 2016-10-09, 2016-10-11, 2016-10-12, 2016-10-30, 2016-12-12, 2016-12-25, 2017-01-26, 2017-03-29, 2017-04-01, 2017-04-05, 2017-04-14, 2017-05-01, 2017-06-26, 2017-08-15, 2017-08-25, 2017-09-02, 2017-09-29, 2017-09-30, 2017-10-02, 2017-10-19, 2017-11-04, 2017-12-01, 2017-12-25
Arunachal Pradesh	2015-01-14, 2015-01-20, 2015-01-26, 2015-03-06, 2015-04-03, 2015-04-15, 2015-05-04, 2015-07-18, 2015-08-15, 2015-10-02, 2015-10-22, 2015-11-11, 2015-11-25, 2015-12-01, 2015-12-25
Assam	2015-01-14, 2015-01-26, 2015-03-05, 2015-04-03, 2015-04-14, 2015-04-15, 2015-05-01, 2015-07-18, 2015-08-15, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-23, 2015-11-10, 2015-11-25, 2015-12-25, 2017-01-14, 2017-01-26, 2017-03-12, 2017-04-14, 2017-04-15, 2017-05-01, 2017-06-26, 2017-08-15, 2017-09-02, 2017-09-29, 2017-09-30, 2017-10-02, 2017-10-18, 2017-10-19, 2017-11-04, 2017-12-25
Bihar	2015-01-26, 2015-03-05, 2015-03-06, 2015-03-22, 2015-03-28, 2015-04-03, 2015-04-14, 2015-05-01, 2015-07-18, 2015-08-15, 2015-09-05, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-23, 2015-10-24, 2015-11-11, 2015-11-17, 2015-11-18, 2015-12-25, 2016-01-26, 2016-03-22, 2016-03-23, 2016-03-24, 2016-03-25, 2016-04-14, 2016-04-15, 2016-05-01, 2016-07-06, 2016-08-15, 2016-08-25, 2016-09-13, 2016-10-02, 2016-10-10, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-06, 2016-11-07, 2016-12-25, 2017-01-26, 2017-03-13, 2017-03-14, 2017-03-22, 2017-04-05, 2017-04-14, 2017-05-01, 2017-06-26, 2017-08-14, 2017-08-15, 2017-09-02, 2017-09-29, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-19, 2017-10-26, 2017-10-27, 2017-12-25

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Table A1 – continued from previous page

State	Date
Chandigarh	2015-01-05, 2015-01-26, 2015-02-03, 2015-02-17, 2015-03-06, 2015-04-02, 2015-04-03, 2015-08-15, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-27, 2015-11-11, 2015-11-25, 2015-12-25, 2017-01-05, 2017-01-26, 2017-02-10, 2017-02-24, 2017-03-13, 2017-04-01, 2017-04-04, 2017-04-13, 2017-04-14, 2017-06-26, 2017-08-15, 2017-10-02, 2017-10-05, 2017-10-19, 2017-11-04, 2017-12-25
Chhattisgarh	2015-01-04, 2015-01-26, 2015-02-17, 2015-03-06, 2015-04-02, 2015-05-04, 2015-07-18, 2015-08-15, 2015-09-05, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-25, 2015-12-24, 2015-12-25, 2016-01-26, 2016-03-07, 2016-03-23, 2016-03-24, 2016-03-25, 2016-04-19, 2016-04-20, 2016-05-21, 2016-07-06, 2016-08-15, 2016-08-25, 2016-09-05, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-14, 2016-12-12, 2016-12-19, 2016-12-25
Dadra & Nagar Haveli	2016-01-26, 2016-03-24, 2016-03-25, 2016-04-20, 2016-07-06, 2016-08-02, 2016-08-15, 2016-09-05, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-14, 2016-12-12, 2016-12-25
Delhi	2015-01-26, 2015-03-06, 2015-04-02, 2015-05-04, 2015-07-18, 2015-08-15, 2015-09-05, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-25, 2015-12-24, 2015-12-25, 2016-01-26, 2016-03-24, 2016-03-25, 2016-04-20, 2016-05-21, 2016-07-06, 2016-08-15, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-14, 2016-12-12, 2016-12-25, 2017-01-26, 2017-03-13, 2017-04-01, 2017-04-09, 2017-04-14, 2017-05-10, 2017-06-26, 2017-08-15, 2017-09-02, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-19, 2017-11-04, 2017-12-02, 2017-12-25
Goa	2015-01-26, 2015-03-06, 2015-03-21, 2015-04-03, 2015-04-14, 2015-05-01, 2015-07-18, 2015-08-15, 2015-09-17, 2015-09-18, 2015-09-25, 2015-10-02, 2015-10-22, 2015-11-10, 2015-12-03, 2015-12-19, 2015-12-25, 2016-01-26, 2016-03-24, 2016-03-25, 2016-04-08, 2016-04-14, 2016-05-01, 2016-07-07, 2016-08-15, 2016-09-05, 2016-09-06, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-29, 2016-12-03, 2016-12-19, 2016-12-25, 2017-01-26, 2017-03-13, 2017-03-28, 2017-04-01, 2017-04-14, 2017-05-01, 2017-06-26, 2017-08-15, 2017-08-25, 2017-08-26, 2017-09-02, 2017-09-30, 2017-10-02, 2017-10-18, 2017-12-04, 2017-12-19, 2017-12-25

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Table A1 – continued from previous page

State	Date
Gujarat	2015-01-04, 2015-01-14, 2015-01-26, 2015-03-06, 2015-04-14, 2015-07-18, 2015-08-15, 2015-08-29, 2015-09-17, 2015-09-25, 2015-10-02, 2015-10-22, 2015-11-11, 2015-11-12, 2015-12-24, 2015-12-25, 2016-01-14, 2016-01-26, 2016-03-07, 2016-03-24, 2016-04-14, 2016-04-15, 2016-07-06, 2016-08-15, 2016-08-18, 2016-08-25, 2016-09-05, 2016-10-11, 2016-10-31, 2016-11-01, 2016-12-12, 2017-01-14, 2017-01-26, 2017-02-24, 2017-03-13, 2017-04-01, 2017-04-04, 2017-04-14, 2017-06-26, 2017-08-07, 2017-08-15, 2017-08-25, 2017-09-02, 2017-09-30, 2017-10-02, 2017-10-19, 2017-10-20, 2017-12-02, 2017-12-25
Haryana	2015-01-26, 2015-02-03, 2015-02-17, 2015-04-02, 2015-04-14, 2015-07-18, 2015-08-15, 2015-09-05, 2015-10-02, 2015-10-22, 2015-10-27, 2015-11-11, 2015-11-25, 2015-12-25, 2016-01-26, 2016-02-22, 2016-03-06, 2016-03-07, 2016-03-24, 2016-04-14, 2016-04-20, 2016-05-21, 2016-07-06, 2016-08-15, 2016-08-25, 2016-10-02, 2016-10-11, 2016-10-30, 2016-11-14, 2016-12-25, 2017-01-26, 2017-02-10, 2017-02-24, 2017-03-13, 2017-04-01, 2017-04-09, 2017-04-14, 2017-05-10, 2017-06-26, 2017-08-15, 2017-09-30, 2017-10-02, 2017-10-19, 2017-11-04, 2017-12-25
Himachal Pradesh	2015-01-26, 2015-02-03, 2015-03-06, 2015-03-28, 2015-04-15, 2015-05-04, 2015-07-18, 2015-08-15, 2015-08-29, 2015-09-05, 2015-09-25, 2015-10-02, 2015-10-24, 2015-10-27, 2015-10-30, 2015-11-11, 2015-11-13, 2015-12-25, 2016-01-16, 2016-01-26, 2016-02-22, 2016-03-07, 2016-03-24, 2016-04-15, 2016-05-21, 2016-06-07, 2016-07-06, 2016-08-15, 2016-08-18, 2016-08-25, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-19, 2016-10-30, 2016-11-01, 2017-01-05, 2017-01-26, 2017-02-10, 2017-02-24, 2017-03-13, 2017-04-01, 2017-04-04, 2017-04-15, 2017-05-10, 2017-06-26, 2017-08-07, 2017-08-15, 2017-09-02, 2017-09-30, 2017-10-02, 2017-10-08, 2017-10-19, 2017-10-21, 2017-11-04

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Table A1 – continued from previous page

State	Date
Jammu & Kashmir	2015-01-04, 2015-01-09, 2015-01-26, 2015-02-17, 2015-03-05, 2015-03-21, 2015-04-14, 2015-05-04, 2015-07-05, 2015-07-13, 2015-07-15, 2015-07-17, 2015-07-18, 2015-08-15, 2015-09-05, 2015-09-25, 2015-09-26, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-25, 2015-12-05, 2015-12-25, 2016-01-26, 2016-03-07, 2016-03-23, 2016-04-08, 2016-04-13, 2016-04-14, 2016-05-21, 2016-07-01, 2016-07-03, 2016-07-05, 2016-07-07, 2016-07-13, 2016-08-15, 2016-08-25, 2016-09-13, 2016-09-14, 2016-10-02, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-25, 2016-12-05, 2016-12-12, 2016-12-16, 2016-12-25, 2017-01-26, 2017-02-24, 2017-03-12, 2017-03-28, 2017-04-01, 2017-04-13, 2017-04-14, 2017-05-10, 2017-06-22, 2017-06-23, 2017-06-26, 2017-07-05, 2017-07-13, 2017-08-15, 2017-09-02, 2017-09-03, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-19, 2017-11-04, 2017-12-01, 2017-12-05, 2017-12-08, 2017-12-25
Jharkhand	2015-01-04, 2015-01-26, 2015-03-06, 2015-03-23, 2015-03-28, 2015-04-02, 2015-04-03, 2015-05-04, 2015-07-18, 2015-08-15, 2015-09-24, 2015-09-25, 2015-10-02, 2015-10-21, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-17, 2015-11-25, 2015-12-24, 2015-12-25, 2016-01-26, 2016-03-07, 2016-03-22, 2016-03-24, 2016-03-25, 2016-04-14, 2016-04-15, 2016-04-19, 2016-05-21, 2016-07-06, 2016-08-15, 2016-08-25, 2016-09-13, 2016-10-02, 2016-10-10, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-14, 2016-12-12, 2016-12-25, 2017-01-26, 2017-02-24, 2017-03-13, 2017-03-30, 2017-04-01, 2017-04-04, 2017-04-14, 2017-05-10, 2017-06-26, 2017-08-15, 2017-09-02, 2017-09-28, 2017-09-29, 2017-09-30, 2017-10-02, 2017-10-19, 2017-10-26, 2017-11-04, 2017-12-02, 2017-12-25
Karnataka	2015-01-04, 2015-01-15, 2015-01-26, 2015-02-17, 2015-03-21, 2015-04-02, 2015-04-03, 2015-04-14, 2015-04-21, 2015-05-01, 2015-07-18, 2015-08-15, 2015-09-17, 2015-09-24, 2015-10-02, 2015-10-12, 2015-10-22, 2015-10-23, 2015-10-24, 2015-10-27, 2015-11-01, 2015-11-10, 2015-11-12, 2015-11-18, 2015-12-24, 2015-12-25, 2016-01-15, 2016-01-26, 2016-03-07, 2016-03-25, 2016-04-08, 2016-04-14, 2016-04-19, 2016-05-01, 2016-05-09, 2016-07-06, 2016-08-15, 2016-09-05, 2016-09-13, 2016-09-30, 2016-10-02, 2016-10-10, 2016-10-11, 2016-10-12, 2016-10-15, 2016-10-29, 2016-10-31, 2016-11-01, 2016-11-17, 2016-12-12, 2016-12-25, 2017-01-14, 2017-01-26, 2017-02-24, 2017-03-29, 2017-04-14, 2017-04-29, 2017-05-01, 2017-06-26, 2017-08-15, 2017-08-25, 2017-09-02, 2017-09-19, 2017-09-30, 2017-10-02, 2017-10-05, 2017-10-18, 2017-10-20, 2017-11-01, 2017-11-06, 2017-12-01, 2017-12-25

Continued on next page

Table A1 – continued from previous page

State	Date
Kerala	2015-01-03, 2015-01-26, 2015-02-17, 2015-04-03, 2015-04-05, 2015-04-14, 2015-04-15, 2015-05-01, 2015-07-18, 2015-08-15, 2015-08-27, 2015-08-28, 2015-08-30, 2015-09-21, 2015-09-24, 2015-10-02, 2015-10-22, 2015-10-23, 2015-11-10, 2015-12-25, 2016-01-26, 2016-03-07, 2016-03-25, 2016-03-27, 2016-04-14, 2016-05-01, 2016-07-06, 2016-08-15, 2016-09-13, 2016-09-14, 2016-09-16, 2016-09-21, 2016-10-02, 2016-10-10, 2016-10-11, 2016-10-29, 2016-12-12, 2016-12-25, 2017-01-26, 2017-02-24, 2017-04-01, 2017-04-14, 2017-04-16, 2017-05-01, 2017-06-25, 2017-08-15, 2017-09-01, 2017-09-03, 2017-09-04, 2017-09-06, 2017-09-21, 2017-09-29, 2017-09-30, 2017-10-02, 2017-10-18, 2017-12-02, 2017-12-25
Madhya Pradesh	2015-01-04, 2015-01-26, 2015-02-17, 2015-03-06, 2015-03-28, 2015-04-02, 2015-05-04, 2015-07-18, 2015-08-15, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-25, 2015-12-25, 2016-01-26, 2016-03-07, 2016-03-23, 2016-04-15, 2016-04-19, 2016-05-21, 2016-07-06, 2016-08-15, 2016-08-18, 2016-08-25, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-14, 2016-12-12, 2016-12-25, 2017-01-26, 2017-03-13, 2017-04-01, 2017-04-05, 2017-04-14, 2017-05-10, 2017-06-26, 2017-08-07, 2017-08-15, 2017-09-02, 2017-09-30, 2017-10-02, 2017-10-19, 2017-11-04, 2017-12-02, 2017-12-25
Maharashtra	2015-01-04, 2015-01-26, 2015-02-17, 2015-02-19, 2015-03-06, 2015-03-21, 2015-03-28, 2015-04-02, 2015-04-03, 2015-04-14, 2015-05-01, 2015-05-04, 2015-07-18, 2015-08-15, 2015-08-18, 2015-09-17, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-12, 2015-11-25, 2015-12-24, 2015-12-25, 2016-01-26, 2016-02-19, 2016-03-07, 2016-03-24, 2016-03-25, 2016-04-08, 2016-04-14, 2016-04-15, 2016-04-19, 2016-05-01, 2016-05-21, 2016-07-06, 2016-08-15, 2016-08-17, 2016-09-05, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-12, 2016-10-30, 2016-10-31, 2016-11-14, 2016-12-12, 2016-12-25, 2017-01-26, 2017-02-19, 2017-02-24, 2017-03-13, 2017-03-28, 2017-04-01, 2017-04-04, 2017-04-09, 2017-04-14, 2017-05-01, 2017-05-10, 2017-06-26, 2017-08-15, 2017-08-17, 2017-08-25, 2017-09-02, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-19, 2017-10-20, 2017-11-04, 2017-12-01, 2017-12-25

Continued on next page

Table A1 – continued from previous page

State	Date
Manipur	2015-01-01, 2015-01-03, 2015-01-26, 2015-02-15, 2015-03-06, 2015-03-21, 2015-04-03, 2015-04-14, 2015-05-01, 2015-07-18, 2015-08-13, 2015-08-15, 2015-10-02, 2015-10-21, 2015-11-01, 2015-11-11, 2015-11-13, 2015-12-25, 2016-01-01, 2016-01-22, 2016-01-26, 2016-02-15, 2016-03-23, 2016-03-25, 2016-04-08, 2016-04-13, 2016-05-01, 2016-07-06, 2016-08-13, 2016-08-15, 2016-08-25, 2016-10-02, 2016-10-09, 2016-10-30, 2016-11-01, 2016-12-12, 2016-12-25, 2016-12-26, 2016-12-31
Meghalaya	2015-01-01, 2015-01-26, 2015-03-06, 2015-04-03, 2015-07-11, 2015-07-17, 2015-07-18, 2015-08-15, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-23, 2015-11-06, 2015-11-11, 2015-11-23, 2015-12-12, 2015-12-18, 2015-12-25, 2015-12-26, 2015-12-30
Mizoram	2015-01-01, 2015-01-02, 2015-01-26, 2015-02-20, 2015-03-06, 2015-04-03, 2015-05-04, 2015-06-15, 2015-06-30, 2015-07-18, 2015-08-15, 2015-10-02, 2015-10-22, 2015-11-11, 2015-12-24, 2015-12-25, 2015-12-26, 2015-12-31
Nagaland	2015-01-01, 2015-01-26, 2015-04-03, 2015-07-18, 2015-08-15, 2015-09-25, 2015-10-02, 2015-10-21, 2015-10-22, 2015-11-11, 2015-11-25, 2015-12-01, 2015-12-24, 2015-12-25, 2015-12-26, 2015-12-27
Orissa	2015-01-24, 2015-01-26, 2015-02-17, 2015-03-06, 2015-03-28, 2015-04-03, 2015-04-14, 2015-07-18, 2015-08-15, 2015-09-05, 2015-09-17, 2015-09-18, 2015-10-02, 2015-10-21, 2015-10-23, 2015-10-24, 2015-11-11, 2015-12-25, 2016-01-26, 2016-02-12, 2016-03-07, 2016-03-24, 2016-03-25, 2016-04-13, 2016-04-14, 2016-04-15, 2016-06-15, 2016-07-06, 2016-07-07, 2016-08-15, 2016-08-25, 2016-09-05, 2016-09-06, 2016-10-02, 2016-10-09, 2016-10-11, 2016-10-12, 2016-10-20, 2016-12-25, 2017-01-26, 2017-02-01, 2017-02-24, 2017-03-13, 2017-04-01, 2017-04-04, 2017-04-14, 2017-06-15, 2017-06-26, 2017-08-14, 2017-08-15, 2017-08-25, 2017-09-02, 2017-09-19, 2017-09-29, 2017-09-30, 2017-10-02, 2017-10-05, 2017-10-19, 2017-12-25
Pondicherry	2015-01-01, 2015-01-03, 2015-01-15, 2015-01-16, 2015-01-26, 2015-04-03, 2015-04-14, 2015-05-01, 2015-07-18, 2015-08-15, 2015-08-16, 2015-09-17, 2015-09-24, 2015-10-02, 2015-10-10, 2015-10-21, 2015-11-01, 2015-11-10, 2015-12-24, 2015-12-25, 2016-01-01, 2016-01-15, 2016-01-16, 2016-01-26, 2016-03-25, 2016-04-14, 2016-07-07, 2016-08-15, 2016-08-16, 2016-09-05, 2016-09-13, 2016-10-02, 2016-10-29, 2016-11-01, 2016-12-12, 2016-12-25

Continued on next page

Table A1 – continued from previous page

State	Date
Punjab	2015-01-26, 2015-02-03, 2015-03-06, 2015-03-28, 2015-05-22, 2015-07-18, 2015-08-15, 2015-09-05, 2015-10-02, 2015-10-22, 2015-10-27, 2015-11-11, 2015-11-25, 2015-12-25, 2016-01-16, 2016-01-26, 2016-02-22, 2016-03-24, 2016-04-15, 2016-06-08, 2016-07-06, 2016-08-15, 2016-08-25, 2016-10-02, 2016-10-11, 2016-10-16, 2016-10-30, 2016-11-14, 2016-12-25, 2017-01-05, 2017-01-26, 2017-02-10, 2017-03-13, 2017-04-01, 2017-04-04, 2017-06-16, 2017-06-26, 2017-08-15, 2017-09-30, 2017-10-02, 2017-10-05, 2017-10-19, 2017-11-04, 2017-12-25
Rajasthan	2015-01-26, 2015-03-06, 2015-04-02, 2015-04-14, 2015-07-18, 2015-08-15, 2015-08-29, 2015-09-25, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-25, 2015-12-25, 2016-01-26, 2016-03-24, 2016-04-14, 2016-04-15, 2016-04-19, 2016-07-06, 2016-08-15, 2016-08-18, 2016-08-25, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-12, 2016-10-30, 2016-10-31, 2016-11-14, 2016-12-25, 2017-01-26, 2017-03-13, 2017-04-01, 2017-04-04, 2017-04-14, 2017-06-26, 2017-08-07, 2017-08-15, 2017-09-02, 2017-09-30, 2017-10-02, 2017-10-19, 2017-10-20, 2017-11-04, 2017-12-25
Sikkim	2015-01-01, 2015-01-14, 2015-01-24, 2015-01-26, 2015-02-19, 2015-03-06, 2015-03-28, 2015-04-03, 2015-04-14, 2015-05-01, 2015-05-16, 2015-06-02, 2015-07-13, 2015-07-18, 2015-08-15, 2015-09-05, 2015-10-02, 2015-11-11, 2015-11-13, 2015-12-12, 2015-12-22, 2015-12-23, 2015-12-24, 2015-12-25
Tamil Nadu	2015-01-01, 2015-01-04, 2015-01-15, 2015-01-16, 2015-01-17, 2015-01-26, 2015-03-21, 2015-04-02, 2015-04-03, 2015-04-14, 2015-05-01, 2015-07-18, 2015-08-15, 2015-09-05, 2015-09-17, 2015-09-24, 2015-10-02, 2015-10-21, 2015-10-22, 2015-10-23, 2015-11-10, 2015-12-23, 2015-12-25, 2016-01-01, 2016-01-15, 2016-01-16, 2016-01-17, 2016-01-26, 2016-03-25, 2016-04-08, 2016-04-14, 2016-04-19, 2016-05-01, 2016-07-07, 2016-08-15, 2016-08-25, 2016-09-05, 2016-09-13, 2016-10-02, 2016-10-10, 2016-10-11, 2016-10-12, 2016-10-29, 2016-12-12, 2016-12-25, 2017-01-01, 2017-01-14, 2017-01-15, 2017-01-16, 2017-01-26, 2017-03-29, 2017-04-01, 2017-04-09, 2017-04-14, 2017-05-01, 2017-06-26, 2017-08-14, 2017-08-15, 2017-08-25, 2017-09-02, 2017-09-29, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-18, 2017-12-01, 2017-12-25

Continued on next page

Table A1 – continued from previous page

State	Date
Telangana	2015-01-04, 2015-01-15, 2015-01-26, 2015-02-17, 2015-03-21, 2015-04-03, 2015-04-05, 2015-04-14, 2015-07-18, 2015-08-15, 2015-09-17, 2015-09-24, 2015-10-02, 2015-10-22, 2015-10-24, 2015-11-11, 2015-12-25, 2016-01-15, 2016-01-26, 2016-03-07, 2016-03-23, 2016-04-05, 2016-04-08, 2016-04-14, 2016-04-15, 2016-05-01, 2016-07-06, 2016-08-15, 2016-08-25, 2016-09-05, 2016-10-02, 2016-10-09, 2016-10-11, 2016-10-12, 2016-10-30, 2016-11-14, 2016-12-12, 2016-12-25, 2017-01-14, 2017-01-26, 2017-02-24, 2017-03-12, 2017-03-29, 2017-04-01, 2017-04-05, 2017-04-14, 2017-05-01, 2017-06-26, 2017-08-15, 2017-08-25, 2017-09-02, 2017-09-29, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-19, 2017-11-04, 2017-12-01, 2017-12-25
Tripura	2015-01-23, 2015-01-26, 2015-04-14, 2015-04-15, 2015-04-21, 2015-05-01, 2015-07-18, 2015-07-24, 2015-08-08, 2015-08-15, 2015-09-25, 2015-10-02, 2015-10-12, 2015-10-20, 2015-10-21, 2015-10-22, 2015-10-24, 2015-10-26, 2015-11-11, 2015-12-25, 2016-01-26, 2016-02-12, 2016-04-13, 2016-04-14, 2016-04-20, 2016-07-06, 2016-07-12, 2016-07-26, 2016-08-15, 2016-09-13, 2016-09-30, 2016-10-02, 2016-10-10, 2016-10-11, 2016-10-12, 2016-10-15, 2016-10-29
Uttar Pradesh	2015-01-04, 2015-01-26, 2015-02-17, 2015-03-05, 2015-03-06, 2015-03-28, 2015-04-02, 2015-04-03, 2015-04-14, 2015-05-03, 2015-05-04, 2015-07-18, 2015-08-15, 2015-08-29, 2015-09-05, 2015-09-25, 2015-10-02, 2015-10-21, 2015-10-22, 2015-10-24, 2015-11-11, 2015-11-12, 2015-11-13, 2015-11-25, 2015-12-25, 2016-01-26, 2016-03-07, 2016-03-23, 2016-03-24, 2016-03-25, 2016-04-14, 2016-04-15, 2016-04-20, 2016-04-21, 2016-05-21, 2016-07-06, 2016-08-15, 2016-08-18, 2016-08-25, 2016-09-13, 2016-10-02, 2016-10-10, 2016-10-11, 2016-10-12, 2016-10-30, 2016-10-31, 2016-11-01, 2016-11-14, 2016-12-12, 2016-12-25, 2017-01-26, 2017-02-24, 2017-03-12, 2017-03-13, 2017-04-04, 2017-04-09, 2017-04-11, 2017-04-14, 2017-05-10, 2017-06-26, 2017-08-07, 2017-08-15, 2017-09-02, 2017-09-29, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-19, 2017-10-20, 2017-10-21, 2017-11-04, 2017-12-02, 2017-12-25

Continued on next page

Table A1 – continued from previous page

State	Date
Uttarakhand	2015-01-04, 2015-01-26, 2015-02-17, 2015-03-05, 2015-03-06, 2015-03-28, 2015-04-03, 2015-04-14, 2015-05-04, 2015-07-18, 2015-08-15, 2015-08-29, 2015-09-05, 2015-09-25, 2015-10-02, 2015-10-22, 2015-11-11, 2015-11-12, 2015-11-13, 2015-11-25, 2015-12-25, 2016-01-26, 2016-03-07, 2016-03-23, 2016-03-24, 2016-03-25, 2016-04-15, 2016-05-21, 2016-07-06, 2016-08-15, 2016-08-18, 2016-08-25, 2016-09-13, 2016-10-02, 2016-10-11, 2016-10-30, 2016-10-31, 2016-11-01, 2016-11-14, 2016-12-12, 2016-12-25, 2017-01-26, 2017-02-24, 2017-03-12, 2017-03-13, 2017-04-01, 2017-04-04, 2017-04-14, 2017-05-10, 2017-06-26, 2017-08-07, 2017-08-15, 2017-09-02, 2017-09-30, 2017-10-02, 2017-10-19, 2017-10-20, 2017-10-21, 2017-11-04, 2017-12-02, 2017-12-25
West Bengal	2015-01-12, 2015-01-23, 2015-01-25, 2015-01-26, 2015-03-05, 2015-04-03, 2015-04-14, 2015-04-15, 2015-05-01, 2015-05-09, 2015-07-18, 2015-08-15, 2015-09-25, 2015-10-02, 2015-10-12, 2015-10-20, 2015-10-21, 2015-10-22, 2015-10-24, 2015-10-26, 2015-11-10, 2015-11-25, 2015-12-25, 2016-01-12, 2016-01-23, 2016-01-26, 2016-02-13, 2016-03-23, 2016-03-25, 2016-04-14, 2016-05-01, 2016-05-08, 2016-07-06, 2016-08-15, 2016-09-13, 2016-09-30, 2016-10-02, 2016-10-08, 2016-10-09, 2016-10-10, 2016-10-11, 2016-10-12, 2016-10-15, 2016-10-29, 2016-11-14, 2016-12-25, 2017-01-12, 2017-01-23, 2017-01-26, 2017-02-01, 2017-03-12, 2017-04-14, 2017-05-01, 2017-05-09, 2017-06-26, 2017-08-15, 2017-09-02, 2017-09-19, 2017-09-27, 2017-09-28, 2017-09-29, 2017-09-30, 2017-10-01, 2017-10-02, 2017-10-05, 2017-10-19, 2017-11-04, 2017-12-25

Note: This table lists all bank holidays at each state from 2015 to 2017.

Table A2
NSE Holidays

Year	Holiday Dates
2015	01/26, 02/17, 03/06, 04/02, 04/03, 04/14, 05/01, 09/17, 09/25, 10/02, 10/22, 11/11, 11/12, 11/25, 12/25
2016	01/26, 03/07, 03/24, 03/25, 04/14, 04/15, 04/19, 07/06, 08/15, 09/05, 09/13, 10/11, 10/12, 10/31, 11/14
2017	01/26, 02/24, 03/13, 03/28, 04/04, 04/14, 05/01, 05/10, 06/26, 08/15, 08/17, 08/25, 10/02, 10/19, 10/20, 12/01, 12/25

Note: This table presents the National Stock Exchange (NSE) holidays for the years 2015 through 2017.

Table A3
Balance Test for UPI Bartik

Variable	(1) High UPI Bartik N	Mean/(SE)	(2) Low UPI Bartik N	Mean/(SE)	(1-2) Pairwise t-test Mean Difference
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)	
Growth in Number of Transactions	204,638	0.177	202,416	0.314	-0.137
		(1.616)		(2.705)	
Growth in Number of Investors	204,638	0.045	202,416	0.049	-0.004
		(0.371)		(0.48)	
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)	

This table compares ex-ante differences in key variables for high low values of Bartik UPI for the period of January 2015 to June 2016. Key variables include levels of economic activity as proxied by night-light intensity, stock market activity as proxied by the number of transactions, number of investors; growth in the number of transactions, and growth in number of investors. UPI Bartik is calculated as the product of the national UPI over time and the pincode-level UPI-GDP measured as September 2017. The average for the high-UPI Bartik (column 2), low-UPI Bartik (column 2), and the difference between the two (column 3) is shown.

Table A4
Effects of UPI on Stock Market Participation: Placebo Test

Randomization Runs	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

This table presents the results of a placebo test using difference-in-difference (DiD) estimates to assess the impact of UPI exposure on stock market participation at the regional (pincode) level. Columns 1 and 2 report estimates based on 100 randomizations, while Columns 3 and 4 present results from 500 randomizations. The unit of observation is the pincode-month, covering the period from January 2015 to January 2020. The dependent variable in columns 1 and 3 is the *Number of Transactions* 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, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 onward. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.

Table A5
Effects of UPI on Stock Market Participation: Placebo Test – Institutional Investors

DV	Number of Transactions	Number of Investors
	(1)	(2)
UPI Exposure X Post	11.859	0.466
	(7.625)	(0.319)
Pincode FE	Y	Y
District-Month FE	Y	Y
N	193,597	193,602
Adj.-R2	0.913	0.943

This table presents the results of a placebo test using difference-in-difference (DiD) estimates to assess the impact of UPI exposure on stock market participation of *institutional investors* at the regional (pincode) level. The unit of observation is the pincode-month, covering the period from January 2015 to January 2020. Column 1 presents the results for *Number of Transactions*, while columns 2 presents the results for *Number of Investors*. UPI exposure is a continuous variable that measures the regional exposure, as defined in equation 1. The variable *Post* is a dummy variable equal to 1 from Q3 2016 onward. All regressions include pincode and district-month fixed effects, as indicated. Standard errors are clustered at the pincode level and reported in parentheses.