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CROSS-PLATFORM DIGITAL PAYMENTS AND CUSTOMER-DRIVEN DATA SHARING: IMPLICATIONS FOR CREDIT ACCESS

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ABSTRACT

Does the ability to generate verifiable digital financial histories, for payments across apps and banks, improve credit access? We answer this using India’s launch of a cross-platform digital payment infrastructure (UPI). Using rarely available data on the universe of consumer loans, we show credit increases by both fintechs (new entrants) and banks (incumbents), on the intensive and extensive margin, to subprime and new-to-credit customers. We show several mechanisms at play: low-cost internet improves credit access, lenders weigh in digital histories, newly established bank accounts matter, and customer-driven digital data sharing across platforms enables access to formal credit.

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Financial inclusion remains a key reform agenda for policymakers across the world. Although household access to savings accounts has improved substantially in the past decade, access to credit continues to elude many newly banked populations due to insufficient or non-existent credit histories (Bachas et al., 2018; Chioda et al., 2024; D'Andrea and Limodio, 2024).[1] Fintechs provide a possible solution: by using alternate data and through novel credit scoring models, they can expand credit to unserved and underserved markets. However, till date there is limited evidence that fintechs promote financial inclusion as they seem to primarily cater to financially included borrowers.

In this study, we examine whether establishing a digital infrastructure that allows payments to be done seamlessly and costlessly across apps and banks can help expand access to credit. Potential borrowers can create a verifiable digital trail of transactions at low or no costs that financial intermediaries can use to assess borrower creditworthiness. This can lower underwriting costs and expand credit access.

We use India's 2016 launch of the Unified Payments Interface (UPI) — a public digital payment infrastructure — as a natural experiment to study these questions. UPI is one of the earliest large-scale deployments of a zero-cost-to-consumer payment system that generates real-time digital financial footprints (Berg et al., 2020). The UPI infrastructure allows cross-platform digital payments, and customers can seamlessly transact across any banking or third-party applications. To fix ideas, a customer on "Google Pay," a popular UPI payment application, can move funds from bank A to a customer or merchant account at Bank B without the need to log on to the respective banks' native applications.[2] Specifically, users are not locked within an app, unlike Venmo, Paypal, etc., in the US, and can make payments across platforms using a unified interface. Within a brief period, UPI became the dominant retail payment rail in India, with over 300 million individuals and 50 million merchants using UPI. As of October 2023, nearly 75% of all retail digital payment transactions were through UPI.[3]

UPI also set the stage to allow customers to efficiently share their payment data across financial intermediaries. In 2018, the Reserve Bank of India (RBI) enabled the use of Open Application Programming Interfaces (Open APIs). Open APIs are a set of

[1]TransUnion estimates that about 82% of the adult population (840 million individuals) in India remained credit unserved or underserved in 2022. This is not just an emerging-market phenomenon: a 2022 TransUnion Study finds that even in developed countries like Canada, the unserved/underserved population is 31% of the adult population, while nearly 4.5% and 14.1% of U.S. households remain unbanked and underbanked as of 2021 (Federal Deposit Insurance Corporation, 2021).

[2]In the absence of UPI, a user would have to use the bank's native app (if available), say YONO, for SBI, and could initiate only a one-way transfer —- from SBI to other accounts. With UPI, the user can transfer funds across any bank, say from using the same YONO app in SBI to HDFC.

[3]See GOI Press Release, 2023 and GOI Website, 2023.

standardized rules and tools that enable different financial institutions to securely and efficiently exchange customer data (such as payments and transaction histories). This enabled financial intermediaries to seamlessly access borrowers' payment data lying within other banks' systems with their consent. The customer owns the data so can approve the digital data sharing and apply to multiple banks/fintechs simultaneously for loans at the touch of a button.

We document five main findings. First, digital payments via UPI substantially increased consumer credit access — on both the intensive margin (existing borrowers) and the extensive margin (previously excluded borrowers) — especially for the traditionally underserved. Importantly, credit increases for both the incumbent banks and the new entrants (fintechs). Second, the surge in fintech credit is most pronounced following the adoption of Open APIs by major Indian banks that enabled borrowers to seamlessly share data across financial intermediaries with customer consent. Third, fintech lenders lead the credit increase to new-to-credit borrowers, especially in ex-ante financially excluded regions. Fourth, a complementary empirical design that exploits the 4G rollout of a major telecom provider (which slashed data costs) supports our findings and underscores the importance of low-cost internet access as a complement to digital payments for fostering credit inclusion. Fifth, using detailed loan-level data from a major fintech lender, we provide direct evidence that lenders incorporate UPI transaction histories into their credit assessment and approval decisions. Finally, the expansion in credit does not translate to higher defaults (controlling for borrower risk) -—- suggesting that this new information helped identify creditworthy but underserved customers. Ours is the first large sample study examining the impact of digital public infrastructure in the form of cross-platform digital payments and Open API-enabled data-sharing on credit markets.

Can a digital payment system, such as the UPI, facilitate credit access to financially excluded markets? Our empirical setting and data are uniquely well-suited to answer this question. India has a large, financially underserved population. Combined with its early public investments in digital payment infrastructure, such as UPI, India offers a unique experimental setting. We obtain and merge multiple proprietary datasets that are rarely available to researchers, including the universe of consumer loans from TransUnion CIBIL at the pincode-month level, regulatory data on deposits from the Reserve Bank of India (RBI) to measure ex-ante UPI exposure, and pincode-level payments data from one of India's top five digital payment service providers (State Bank of India). We have information on credit by lender category (fintechs and banks) and borrower type (new-to-credit, sub-prime, and prime), allowing us to answer our central question on how cross-digital payment platforms affect financial inclusion.

Four additional datasets help us pin down the mechanisms: (i) the timing of adoption of Open-APIs (provisioned by RBI) by major Indian banks obtained through Right-to-Information (RTI) act filings, (ii) regulatory data on previously unbanked accounts (Jan Dhan Yojana, JDY, accounts) from the Department of Financial Services (Government of India), (iii) regulatory data on the location, service provider name, and the date of setting up 4G telecom towers from the Telecom Regulatory Authority of India (TRAI), and (iv) loan-level data from one of the largest fintech lenders in India that lends to roadside kiosks with detailed information on borrower and loan characteristics, including the lender's internal credit score and borrowers' UPI transactions.

Between 2015 and 2019, credit increased rapidly, and fintech credit volume grew nearly 10x in the subprime and new-to-credit segment. A 10% increase in UPI payments is associated with a striking 7% increase in credit. We establish causality by exploiting the staggered adoption of UPI by banks (Dubey and Purnanandam, 2024) in our empirical design and rely on two key insights. First, a bank account is necessary to use the full functionality of UPI. Hence, depositors in regions served by early adopter banks were likely to adopt UPI early on. Second, network externalities in the adoption of digital payments (Crouzet et al., 2023; Higgins, 2024) induce regions served by early adopter banks into further UPI uptake. We exploit these ex-ante neighborhood-level differences in UPI exposure and generate exogenous variation within narrow neighborhoods (pincodes). We construct the ex-ante fraction of deposits (as of March 2016) of early adopter banks in a pincode[4]. Pincodes with above (below) median values are defined as high (low) exposure. High-exposure pincodes exhibit higher UPI usage, thus validating our exposure measure. Univariate balance tests show no statistically significant differences in either pre-UPI levels or growth in economic activity or credit across high- and low-exposure pincodes.

Armed with this measure, we construct a difference-in-differences empirical design that compares high-exposure pincodes (treatment group) — neighborhoods exposed to early adopter banks — to low-exposure pincodes (control group) post-UPI to examine credit outcomes. A unique advantage of our measure is that many government policies operate at the level of administrative geographical units and not the pincode level. This granularity allows us to compare across pincodes within a district, by using district-by-time fixed effects. Pincode fixed effects absorb time-invariant differences between treatment and control groups. To further strengthen our empirical strategy and to ensure other time-varying unobservable factors are not driving our results, we construct granular grids (similar to Moscona et al. (2020)) by dividing the Indian map into rectangular

[4]Pincodes are geographic units used by India Post and similar to zip codes in the US. Districts are a more aggregated geographic unit similar to counties in the US.

units of size 0.4 $\times$ 0.4 degrees. This allows us to control for time-varying factors within very narrow geographies (grids) *within* districts. This further bolsters our empirical design and our baseline estimates are identified through within-grid variation in UPI exposure across pincodes. The identifying assumption as in a canonical difference-in-differences setup requires that treated and control pincodes exhibit similar trends absent treatment, conditional on grid-by-month fixed effects. We find no statistically significant pre-treatment trend differences in credit. In balance tests, we find no discernible pre-treatment differences in economic activity across treated and control pincodes.

We estimate a 15% increase in credit in high-exposure pincodes relative to the pre-treatment mean. Credit increases across borrower risk profiles: subprime, new-to-credit, and prime. In principle, both banks and fintechs can leverage the payment data to lend to underserved households. However, fintechs are lightly regulated, are quicker to adopt technological innovations, are faster at processing loans, and have lower operating costs due to automated online underwriting (Fuster et al., 2019; Seru, 2020). In contrast, traditional intermediaries are more regulated and slower to adopt new technologies (Seru, 2020; Mishra et al., 2022) and may face higher opportunity costs if they specialize in big ticket loans to prime borrowers. Thus, it is important to examine heterogeneity between fintechs and banks. Fintechs' loan value (volume) in high UPI exposure pincodes is 56x (81x) larger than the pre-period mean, partly attributable to the low pre-UPI base. In comparison, bank lending increases by a relatively modest 54% in value and 55% in the number of loans in high exposure pincodes. The number of loans by fintechs to subprime and new-to-credit borrowers increases by 40x and 83x. Bank credit is highest for prime borrowers, with only a muted increase for subprime and new-to-credit borrowers. UPI promotes market segmentation: fintechs target new marginal borrowers rather than compete with banks for the ex-ante included borrowers (Boot and Thakor, 2024).

A key step enabling data sharing was the introduction of Open API in 2018. With customers' consent, both banks and fintechs could instantly access verified transaction data, which lowered information frictions in credit markets. Banks adopted this API-enabled infrastructure voluntarily and in a staggered manner, which we exploit to construct a time-varying measure of API exposure at the pincode-month level. In a triple-differences specification that interacts API exposure with UPI exposure, we capture how credit outcomes respond in regions with both high digital payment activity and increasing API connectivity. Credit expansion — particularly to subprime and new-to-credit borrowers — is strongest in areas with high UPI and high API exposure, underscoring the complementarity between digital payments and open data-sharing infrastructure.

Another crucial element in the credit uptake was the "Jan Dhan Yojana" (JDY) scheme, which was introduced in 2014 as part of India's financial inclusion mission to facilitate savings accounts for the unbanked and boosted bank account access (Agarwal et al., 2017). Since users need a bank account to operate UPI, JDY ensured that the environment was primed for UPI take-off. Fintech loans to new-to-credit borrowers are higher in regions with ex-ante more JDY account holders, that is, regions with ex-ante more new-to-banking customers with no/thin credit history. UPI, thus, complemented savings bank account-oriented financial inclusion programs in expanding credit access.

UPI usage requires access to fast, reliable, and low-cost internet. In 2016, Reliance Jio launched 4G services, improving network coverage and lowering the cost of internet access. Prices for 1 GB of data dropped from ₹228 in 2015 to ₹9 in 2020. The average distance of the pincode centroid to a 4G tower dropped from 15.1 km in 2016 to 2.1 km in 2020. A tower delivers dependable internet within 3–6 kilometers. We exploit the entry of a Jio Tower across pincodes as a source of exogenous variation in cheap and reliable internet access. Fintech credit growth by UPI exposure is differentially higher in early Jio adopter pincodes, with the highest effect for the subsample of new-to-credit borrowers. In contrast, bank lending to new-to-credit borrowers shows no increase. To distinguish between access to 4G vs. cost of internet, we compare treatment effect estimates within the subsample of pincodes with early access to non-Jio towers and find robust effects, highlighting the complementarity between digital inclusion due to low-cost internet access and UPI in expanding credit access to marginal borrowers.

Using loan-level data from a large fintech lender for roadside kiosk owners for 2020-2023, we examine how the lender incorporates UPI transaction information into its lending decisions. Consistent with the baseline, UPI transactions positively correlate with loan amounts and negatively correlate with interest rates. Importantly, UPI transactions positively correlate with the lender's internal credit score, establishing the direct link between the lender's credit assessment decisions and UPI transactions.

Finally, in additional tests, we show that the credit increases do not translate to differentially higher default rates. Thus, UPI-based information enabled lenders to lend to underserved, creditworthy borrowers without taking on additional default risk.

Related literature We contribute to several strands of the literature. First, our paper relates to the financial inclusion literature on access to basic savings accounts (Dupas et al., 2018; Bachas et al., 2021; Breza et al., 2024). However, despite having a bank account many newly banked borrowers without credit histories still struggle to obtain loans (Agarwal et al., 2017). Our findings speak to this gap: usage of bank accounts via a digital payments platform generates a verifiable transaction history and improves credit access.

Second, we contribute to the growing literature on the impact of fintechs on credit markets. See Berg et al. (2022) and Agarwal and Zhang (2020) for a survey of the literature on fintech, lending, and payment innovations. While technology-driven cost savings can expand access to finance, direct empirical evidence remains scarce (e.g., Buchak et al. (2018); Fuster et al. (2019); Bartlett et al. (2022); Balyuk et al. (2022); Gopal and Schnabl (2022); Chioda et al. (2024); Kalda and Neshat (2024)). The fintechs studied in prior literature had to privately invest in technology or partnerships to create alternate data sources to assess customers' credit risk. In our study, the cost of payment infrastructure was borne by NPCI, a quasi-government entity, in India. In our setting, credit increases to traditionally excluded borrowers (new-to-credit and subprime), underscoring the role of digital public payments infrastructure in facilitating credit access.

Third, we add to the literature on consumer welfare implications of broader data sharing and open-data systems in finance including open banking initiatives (Parlour et al., 2022; Goldstein et al., 2023; He et al., 2023; Babina et al., 2024). Ours is the first large sample study of an open payments system in an emerging market to show how consumer's payments data portability translates into improvements in credit access.

Fourth, our work intersects with research on the macroeconomic and credit implications of digital or cashless payment systems (Agarwal et al., 2020; Ouyang, 2022; Sarkisyan, 2023; Dubey and Purnanandam, 2024; Ghosh et al., 2024). Using data from a single fintech entity, some of these papers document that cashless transactions enable credit access. Agarwal et al. (2020) show that the introduction of QR-code payment technology increases new business creation. Similarly, using the UPI-launch as a natural experiment Dubey and Purnanandam (2024) show a positive impact of digital payments on real economic output. Our work complements Dubey and Purnanandam (2024) by providing direct evidence of one potential mechanism through which cashless payments affect real economic activity — by expanding access to credit.

Our work is distinct from other papers on fintech and cashless payments. First, our study provides novel evidence of the effects of a large-scale shift to cashless payments on credit supply to previously underserved borrowers. Second, we examine the impact of Open API-enabled data sharing, wherein the customer can decide whether and to whom to share data and can apply simultaneously to multiple banks or fintechs for credit. Absent such data-sharing arrangements, the fintech or the website exercises its discretion or monopoly power in making credit decisions with plausibly very different aggregate outcomes. Finally, unlike most papers that obtain data from a single fintech, our main tests rely on data from the credit bureau on the universe of consumers, allowing us to examine the effects on credit across different customer profiles and by different intermediaries. In doing so, we reveal an important macro-level linkage: the payment system's technological upgrade translates into a broader credit deepening in the economy.

This study contributes not just to the academic literature but also helps inform policymakers. India's experiment with public investment in digital infrastructure (UPI and Open APIs) has attracted significant attention from policymakers worldwide; drawing comments from Fed policymakers (Yadav, 2024), to the World Bank (The Economic Times, 2023), to Bill Gates (The Indian Express, 2020) as a model with potential lessons for other countries. Despite the significant attention on UPI among policymakers globally, research on the impact of this initiative on credit markets is lacking. Our study fills the gap and provides the first comprehensive analysis of how this unique large-scale experiment — providing open digital payment infrastructure — affects access to credit, and in particular, financial inclusion through first-time access to formal credit markets.

1 Institutional details

UPI In November 2016, the National Payments Corporation of India, officially rolled out the Unified Payments Interface (UPI) all over India for public use. Through UPI, customers and merchants can securely transfer money between bank accounts. Customers can link their bank accounts to mobile applications and transact safely, instantly, securely, and across digital payment platforms (also termed as interoperability). Transactions are protected with end-to-end encryption, which ensures that personal data remains confidential both at the time of the transaction and after its successful completion.

After its launch, UPI transactions rose from 1 million transactions in October 2016 to nearly 10 billion transactions in October 2023. UPI transactions accounted for nearly 75 percent of all retail transaction volume in 2022-23 (Rao, 2023). As per GlobalData research, cash transactions declined from 90 percent of the total volume in 2017 to less than 60 percent in 2021, with UPI and other digital transaction systems accounting for the remaining. A large impetus to UPI uptake was the 2016 demonetization episode, which overnight discontinued 86 percent of cash in circulation. The sudden shortage of cash pushed people into using digital payments as a mode of payment. By the end of 2017, UPI transactions had grown by 900 percent compared to pre-demonetization levels.

Several factors are responsible for the widespread adoption of UPI. UPI facilitates e-commerce, as businesses, merchants, and vendors can seamlessly integrate into the UPI network and accept cashless payments. UPI has also bridged the gap between traditional banking and technology, enabling financial access. Any customer with a bank account can make payments via UPI. Importantly, UPI allows users to create a digital footprint of money flow, which lenders can access, enabling financial inclusion. This last feature has transformed the fintech industry. Several innovations, such as digital wallets, investment platforms, lending apps, expense trackers, and more, have effectively used UPI to provide add-on services. Internet Appendix Figure IA1 describes how UPI allows users to create digital footprints that lenders can use in deciding to lend. Even in the aggregate, there is a strong correlation between credit and UPI at the state level. A 10% increase in UPI is associated with a 7% increase in credit (Figure 1). The rise in UPI allowed lenders, primarily the fintech lenders that operate within the digital realm, to access payment transaction data to determine creditworthiness. Figure IA3 shows the loan application interface for a user using UPI.

UPI infrastructure The underlying technical infrastructure for UPI is complex and costly to build. Internet Appendix Figure IA2 explains the flow of how UPI works. While end-users interact with the consumer-facing interface of the UPI network, only regulated financial institutions can connect to the UPI network. Regulated entities include banking apps and third-party apps — called Third Party Application Providers (TPAPs) — can partner with multiple banks. Examples include CRED, backed by Axis Bank; Google Pay, backed by multiple banks; and BHIM, the official app released by NPCI[5]. The connected banks are called Payment Service Providers (PSP) and are responsible for the onboarding of users, authentication, and registration and for ensuring that the TPAPs are compliant and secure. They also act as a grievance redressal mechanism for resolving complaints. PSPs that have onboarded the Payer are called Payer PSPs, and PSPs that have onboarded the Payee are called the Payee PSP. Each person on the UPI network has a unique address to identify them. When a UPI transaction is initiated, the UPI Switch finds the Payee PSP using the unique address and routes the transaction to the Payee's corresponding PSP. After validation, the transfer of money occurs in real time, unlike card transactions, in which the money moves at the end of the day. UPI can also be used to pay merchants and follows a similar process. Shops have a static QR that can be scanned with the UPI app, and payments can be settled in real-time. Importantly, for the period of our analysis, there was no payment charge for the consumer or the merchant, unlike credit or debit cards, which charge 1-2% as interchange fees.

In 2018, the RBI enabled Open-API, which played an important role in allowing customers to seamlessly share their payment data across financial intermediaries. Open-API is a set of standardized rules and tools that allow financial intermediaries to exchange

[5]See the NPCI website, for the list of approved apps and their connected banks here.

customer data (such as payments and transaction histories) in a secure and efficient manner with the consent of the customer. Data ownership rests with the customer–they can share their UPI payment transaction history, which facilitates cross-institutional credit applications. Bypassing the complexity and frictions involved in many integrations, Open-API allows multiple financial intermediaries to access data lying with traditional banks through a standardized API.[6]. Open APIs are a core element of open payment systems and part of the shift toward open finance and open banking. Open APIs break information monopolies and hold-ups and encourage greater competition in the financial sector. They provide new entrants with the necessary data to develop innovative solutions and expand markets.

Jio rollout Reliance Jio Infocomm Limited, popularly known as Jio, is an Indian mobile network operator. It is owned by Reliance Industries and headquartered in Mumbai, Maharashtra. It operates a national network with coverage across all 22 telecom circles, giving 4G services. The launch of Reliance Jio transformed the Telecom industry. According to the Telecom Regulatory Authority of India (TRAI), as of February 2019, there were 1.17 billion mobile phone subscriptions in India. The growth was especially pronounced in rural areas, with over 500 million wireless subscriptions, roughly 100 million more than before Jio formally began its operations. In September 2016, Jio made its formal entry into the market with a unique proposition — focusing on high-speed data rather than voice and messaging services. Jio offered customers 4G internet with data plans amounting to 1 GB per day. In comparison, its competitors offered only 1 GB of data per month. In addition, initial prices were at just ₹5 per GB compared to ₹250-300 per GB for competitors. Low costs and attractive discounts allowed Jio to expand its market share quickly. By February 2017, Jio had crossed 100 million subscribers.

The Jan Dhan Yojana (JDY) scheme In August 2014, the Pradhan Mantri Jan-Dhan Yojana (JDY), a large-scale universal banking program, was launched with the mission of financial inclusion. The stated goal was to ensure that essential financial services such as savings and deposit accounts and remittances were made affordable, especially to previously financially excluded individuals in India. While previous programs had targeted inclusion based on village-level metrics of banking access, JDY explicitly aimed to provide access to each household. The JDY served as a precursor to the Open Banking digital payments infrastructure. JDY ensured that previously financially excluded parts of the population had a bank account. Over 280 million new bank accounts were opened

[6]See https://www.openpayments.io/

through the JDY scheme (Agarwal et al., 2017). By July 2016, nearly 99% of Indian households had a bank account due to the JDY schemes, ensuring the preconditions for UPI growth were in place.

2 Data and Empirical Strategy

2.1 Data

Our study combines several unique regulatory and proprietary data, rarely made available to researchers. Table A1 describes the main variables and common terms used in our paper.

Credit bureau data Our primary data is from TransUnion CIBIL, India's largest and oldest credit registry amongst 4 bureaus.[7] The 2005 Credit Information Companies Regulation Act was effective on December 14, 2007, and requires financial institutions to submit monthly data on all new loans granted and loan repayments to credit bureaus. The bureaus ensure data integrity through extensive cross-checks and provide universal coverage of all retail lending activity in India (Mishra et al., 2022).

We are fortunate in that our data from TransUnion CIBIL covers the universe of loans. This is aggregated to the pincode level[8] at the monthly frequency for the period October 2015-January 2019. For our analysis, we focus on the consumer loan segment, where alternate data on digital transactions is expected to have the greatest impact. We observe the number of new loans granted, sanctioned loan amount (in billion INR), and loan default within 12 months of issuance by lender type and borrower type. A loan is classified as having defaulted if it is 90 days past due within 12 months of issuance.

Three features of the data make it uniquely suited for our purposes.

First, we observe the type of lender, namely, banks and fintechs. Fintech refers to non-banking financial corporations (NBFCs) that use new-age technologies, such as mobile applications, to deliver financial services. Such disaggregation is important given that recent research suggests that technological shifts are likely to affect banks and fintechs differently (Buchak et al., 2018; Seru, 2020). Being able to observe lender types allows us to examine the relative effects of Open Banking on incumbents, such as banks, compared to new entrants, such as fintechs, a primary focus of this paper.

[7] The remaining three credit information companies bureaus are Equifax, Experian, and CRIF-Highmark.

[8] Pincodes refer to six-digit codes in the Indian postal code system used by India Post and correspond to zip codes in the US. We also use a higher level of aggregation, districts, in our empirical specification, which correspond to geographic administrative units similar to counties in the USA.

Second, we observe borrower's credit risk as indicated by their credit score categories. Credit scores range from 300 to 900, and credit categories are divided into subprime (300 to 680), near-prime (681 to 730), prime (731 to 770), prime-plus (771 to 790), super-prime (791 and above), and new-to-credit. The new-to-credit category represents those borrowers for whom the credit bureau does not have a formal credit history, and hence, this category has the highest information asymmetry between lenders and borrowers. Importantly, for our purposes, the various credit score categories allow us to study how public provision of cross-platform digital payments infrastructure affects financial inclusion through credit access to ex-ante underserved (subprime, below-prime, and new-to-credit) and ex-ante included (prime, prime-plus, and super-prime) borrowers.

Third, our data covers the universe of consumer loans. Since our primary focus is on financial inclusion, universal coverage ensures we capture access to marginal and underserved or unserved households. The sheer scale of our data stands out in stark comparison to studies using Credit Bureau data, such as in the US, that typically are able to access only a small (5%) sample and often lack the level of lender and borrower detail on loans that we have.

We benchmark the aggregate data to publicly available data from the RBI. Data on the gross flow of new credit (new loan originations) is not available from any public source, even at the aggregate level. However, the RBI provides aggregate statistics on total outstanding loans (credit stock). We use this data to estimate annualized net credit flow, which equals new consumer loans granted less consumer loans repaid. Reassuringly, we find an economically meaningful 83% correlation between annualized gross credit flows estimated from our data and the net credit flow estimates obtained from RBI data.[9]

Banks' deposits data Our second important dataset on deposits is from the regulator, RBI. This unique and proprietary data is crucial to construct our pincode-level UPI exposure measure. Our empirical strategy combines two key ingredients: (i) some banks were early to adopt UPI relative to others, and (ii) users need a bank account to make UPI transactions. We leave the details of how the measure is constructed to Section 2.2 and describe the details of the underlying data here. Information on bank-wise UPI adoption is publicly available.[10] Deposits data is from branch-level data from the Basic Statistical Returns (BSR), a branch-level dataset maintained by RBI. Data is at the annual level as of March 31st, the end of the fiscal year. We first map the branches to the pincode and aggregate deposits to the bank-pincode level using data as of March 31st,

[9] Internet Appendix Table IA1 reports these correlations.
[10] Available from Government of India website: http://cashlessindia.gov.in/upi_services.html.

2016, the latest data available before widespread UPI adoption in November 2016. Of particular importance to us is the granularity of the deposit data, which allows us to define pincode-level exposure to UPI adoption and compare neighborhoods within very narrow geographies in the empirical strategy.

Data on payment transactions Our third dataset on UPI transactions is from one of India's largest public sector bank (the State Bank of India (SBI)) and ranks among the top five in terms of UPI market share. We obtain data on both the UPI transaction volume and value in Rupees at each branch of the public sector bank. Since a bank account is required to make a UPI transaction, this data captures all UPI transactions made by the depositors of the Bank. We aggregate the UPI transactions to the pincode-month level for our analysis for the period January 2017 to January 2019. This data is used to validate our measure of UPI exposure. We verify that our proprietary data accurately represents the broader economic trends in UPI usage by comparing it to publicly available national aggregates from the National Payment Corporation of India (NPCI). Reassuringly, there is a 97% correlation between the two data series (Internet Appendix Table IA1), ensuring that we are accurately capturing UPI take-up across time.

Open-API rollout data We also obtain data on bank-wise onboarding of Open API, through a Right to Information Act (RTI) filing.[11] The data demarcates the bank name and the month-year of API onboarding, covering the period November 2017 to December 2018. This is then mapped to bank-branch level data from BSR, whose further mapping to pincodes allows us to compute pincode-time level exposure to API adoption.

Data on Jan Dhan Yojana (JDY) accounts For supplementary analysis, we obtain regulatory data on the number of Jan Dhan Yojana (JDY) accounts opened at the pincode-month level from the Department of Financial Services, Government of India. This data covers the period July 2014-November 2016.

Jio 4G tower data We also obtain proprietary data from the Telecom and Regulatory Authority of India (TRAI) on the location and date of setting up geolocations of all Base Transceiver Stations (BTS) in India. A BTS, which we refer to as a tower, acts as a communication link between the network and user devices (e.g., mobile phones). We restrict to 4G technology towers. Importantly, we know the service providers, namely, Jio,

[11] The Right to Information Act 2005 allows any Indian citizen to request information from a public authority. The authority is mandated to reply to information requests within 30 days.

Airtel, BSNL, and Vodaphone. In September 2016, Jio enabled fast, easy, and cheap access to the internet. Data on Jio towers is used for our baseline analysis, and we use the data on non-Jio towers in placebo tests. Data is for November 2016-January 2019.

Micro data from the largest fintech firm Finally, we supplement our main tests using the Credit Bureau data with analysis with loan-level data from one of the largest Fintech firms in India, catering to very small merchants, such as roadside kiosks. This dataset provides rich data on borrower characteristics, the loan contract, and the lender's internal assessment of the borrower's credit risk profile, allowing us to pin down the mechanism facilitating credit access. The fintech firm focuses on streamlining transaction methods for small enterprises and provides an array of services through their smartphone application and QR code payment platform. These services enable partner merchants to use QR code stickers that customers can easily scan to complete transactions using a variety of digital payment methods, such as UPI, credit/debit cards, and digital wallets, essentially eliminating the need for physical point-of-sale (POS) terminals. This seamless mode of digital payments is valuable to both customers and merchants. The lending arm of the business targets small and medium-sized businesses to offer merchant cash advance (MCA) loans to its partner merchants. We obtain detailed loan-level information on loans granted to small informal roadside kiosks for the period January 2020–October 2023. We observe information on the date of the loan application, the pincode of the applicant, loan size, interest rate, lender-assigned internal credit scores, and the volume and value of transactions made through UPI from their QR platform.

2.2 Exposure measure

The main empirical strategy relies on the staggered adoption of UPI by participating banks. The Government of India lists the early adopter banks that were live on the UPI platform as of 2016 Q3.[12] We generate regional variation in exposure to UPI following the approach in Dubey and Purnanandam (2024) with an important distinction. We access proprietary data on bank deposits at the branch level provided by RBI that allows us to measure UPI exposure at a more granular pincode level. The regional UPI exposure measure relies on two key insights. First, a bank account is necessary to use the full functionality of UPI. Thus, depositors in regions served by early adopter banks were likely to adopt UPI early on. Second, there are significant network externalities in the adoption of digital payments (Crouzet et al., 2023; Higgins, 2024). As depositors in

[12] Available on http://cashlessindia.gov.in/upi_services.html Government of India website.

regions served by early adopter banks increased UPI uptake, it further catalyzed broader regional adoption through these network externalities.

Together, these two insights suggest that the fraction of depositors at early adopter banks in a pincode predicts UPI usage. To construct the exposure measure, we use the data on bank-wise deposits at the pincode-bank level. We take the deposit data as of March 2016, the latest data available before widespread UPI adoption in November 2016. We classify banks that were live on UPI as of 2016 Q3 as 'early' adopter banks since the GoI makes this data publicly available [13].

Formally, we compute the UPI exposure for pincode p as follows:

$$\text{Exposure}_p = \frac{\text{Total deposit accounts of Early Adopter Banks}_p}{\text{Total deposit accounts of all Banks}_p} \tag{1}$$

In our empirical analysis, we classify high exposure pincodes as those with above median values of the exposure measure and as low exposure otherwise.

Importantly, relying on granular pincode-level variation allows us to strengthen our empirical identification on two fronts. First, one concern might be that early adopter banks differ in significant ways from late adopter banks. Alternatively, early adopter banks may choose to be so, anticipating greater adoption or larger peer effects. By focusing on pincode-level variation, we ensure that local differences in high-exposure pincodes, such as local economic conditions or aggregate peer effects that drive UPI adoption or pincode-level characteristics, are not driving the bank-level decision to adopt UPI. Second, a higher level of aggregation, such as at the district level, does not have the same advantage. For example, several social welfare mandates, such as branching regulations and priority sector lending, operate at the district level. If such mandates were particularly binding for certain types of banks (Kulkarni et al., 2023), district-level exposure variation may be contaminated by these bank-level differences. Instead, the granularity of our data allows us to compare pincodes within a district, assuaging such concerns.

However, one could still argue that time-varying factors differentially affect high- and low-exposure pincodes. For instance, high-exposure pincodes could have higher ex-ante economic growth prior to UPI, which may result in higher ex-post UPI transactions and credit outcomes. These concerns are allayed to a large extent as all our empirical specifications rely on within-district comparisons using district$\times$time fixed effects that

[13] Our data on UPI transactions is from SBI, and hence, we exclude SBI from the exposure measure to avoid a mechanical correlation between the two. Our results are robust to including SBI in the exposure measure calculation.

control for time-varying factors at the district level in a non-parametric way. Nonetheless, Appendix Table A2, also shows the balance tests. We examine if exposure measures are correlated with ex-ante differences in economic activity or credit access. Using nightlight intensity at the pincode level as a measure of economic activity, we show that low- and high-exposure pincodes do not vary in the level of economic activity per capita prior to the launch of UPI. Neither do the two regions differ in terms of growth in economic activity. We examine differences in credit access. Reassuringly, we also do not observe any statistically significant difference in level or growth in credit. Since financial inclusion is of particular interest to us, we also examine the heterogeneity in credit access to underserved borrowers, namely the subprime and new-to-credit segment, and find no statistically distinguishable differences between high- and low-exposure pincode. Overall, these tests tell us that our exposure measure is uncorrelated with credit and economic growth.

Does the exposure measure capture actual UPI usage? We examine whether our exposure measure captures variation in UPI usage. Internet Appendix Figure IA4 compares UPI transaction value and volume in low- and high-exposure locations. Consistent with our premise, high-exposure pincodes have persistently greater UPI usage throughout our analysis period. More formally, we estimate the effect of exposure on UPI transactions using the specification:

$$Y_{pd(p)t} = \delta_{gt} + \alpha_{d(p)t} + \beta \times \text{High Exposure}_p + \epsilon_{pd(p)t} \tag{2}$$

for pincode p in district $d(p)$ in month-year t. Observations are at the pincode-month level for January 2017 to January 2019. $Y_{pd(p)t}$ is UPI transaction volume and value. High Exposure$_p$ is a dummy variable that identifies pincodes above median values of exposure measure as defined in Equation (1). The coefficient of interest, β, measures the impact on UPI take-up for areas more exposed to early adopter banks relative to low-exposure pincodes. Standard errors are clustered by pincode. This specification is analogous to examining the first-stage effect relating our exposure measure to UPI transactions.

Appendix Table A3 shows the results. In line with Internet Appendix Figure IA4, column 1 reveals that high-exposure pincodes have an average monthly UPI transaction value of ₹4 million higher than low-exposure pincodes. Relative to the mean of ₹8.967 million, this corresponds to a 48.5% greater UPI volume in high-exposure pincodes. Column 2 shows the relationship between pincode-level UPI exposure and the volume of UPI transactions. The average volume of monthly transactions is higher by 1,700 or by 44% relative to the mean in high-exposure pincodes than in low-exposure pincodes. Overall, these results help validate our measure of treatment intensity and show that high-exposure pincodes indeed capture pincodes with more UPI transactions.

2.3 Descriptive statistics

Table 1 presents the summary statistics for key variables. Early adopter banks have a median (mean) deposit market share of 47% (49%) across pincodes, as indicated by the UPI exposure measure with significant geographic distribution (Panel A, Figure 2) across pincodes. The frequency distribution shows some bunching at the extreme values: out of 12,576 pincodes in our sample, 2,602 pincodes have zero exposure, and 1,049 pincodes have 100 percent exposure (Panel B, Figure 2).

UPI transactions have been exponentially increasing (Internet Appendix Figure IA5), with growth in high-exposure pincodes outpacing low-exposure pincodes (Internet Appendix Figure IA4). At the pincode-by-month level, the mean (median) number of UPI transactions stood at 4 (1) thousand, while the mean (median) value of transactions was ₹9 (₹2) million. Along the credit dimension, the mean (median) number of new loans sanctioned was 93 (21), totaling ₹14 (₹4) million in value. The amount of loans granted to new-to-credit borrowers was nearly ₹2.5 million on average, more than three times that of subprime borrowers (₹0.8 million). On the extensive margin, the mean number of loans to new-to-credit borrowers (23) is almost four times that of subprime loans (5) loans. There is heterogeneity across lenders. Fintechs are smaller players in the market with an average of ₹0.13 million loans compared to banks with an average of ₹13.5 million. Fintechs' have a smaller market share even in terms quantity of loans sanctioned.

Table 2 reports the results of the univariate analysis. Panels A and B show the average increase in the number of loans for fintechs and banks, respectively, pre- and post November 2016.[14] The number of loans increases after UPI adoption for both the high- and low-exposure pincodes across both banks and fintech (columns 3 and 6). Column 7 reports univariate difference-in-differences estimates. Fintech credit is differentially higher in high-exposure regions for all borrowers across the different credit score bands (Panel A). In contrast, consistent with the graphical evidence in 4, we do not observe a differential growth in bank credit to subprime and new-to-credit customers across high- and low-exposure regions (Panel B). Bank credit growth is differentially higher in high-exposure regions only for prime borrowers.

[14]Internet Appendix Table IA2 reports estimates for the loans amounts.

2.4 Main empirical strategy

Our main analysis assesses the impact of UPI exposure on credit outcomes using the following difference-in-differences specification:

$$Y_{pd(p)t} = \alpha_{d(p)t} + \delta_{gt} + \theta_p + \beta \times \text{Post}_t \times \text{High Exposure}_p + \epsilon_{pd(p)t} \tag{3}$$

for pincode p belonging to district $d(p)$ in month-year t. Observations are at the pincode-month-year level from October 2015 to January 2019. Post_t takes a value of 1 from November 2016. The dependent variable, $Y_{pd(p)t}$, is the sanctioned amount (in ₹million) or number of loans. θ_p refers to pincode fixed effects, δ_{gt} refers to grid $\times$ month fixed effects, and $\alpha_{d(p)t}$ refers to the district$\times$month fixed effects. Standard errors are clustered at the pincode level. The coefficient of interest, β, measures the impact on credit for pincodes with high exposure to early adopter banks relative to pincodes with low exposure in the post-period relative to the pre-period.

We control for time-invariant factors within very narrow geographies with the pincode fixed effect. In addition, the district$\times$month fixed effect allows us to control for time-invariant and time-varying factors at the district-month level. Importantly, the treatment effects are identified within district$\times$month across pincodes with varying exposure to early adopter banks. Several bank mandates and social welfare mandates, such as bank branching regulations and priority sector lending requirements, operate at the district level. Since such mandates can be particularly binding for certain types of banks (Kulkarni et al., 2023), district$\times$month fixed effect allows us to compare across pincodes within the same district, holding constant the district-level differences in lending due to such regulations. In addition, since the district-level aggregation captures economically integrated units, we are able to also control for time-varying local economic conditions.

To further control for time-varying factors within narrow geographies *within* districts, we use a strategy similar to Moscona et al. (2020). We construct grids by dividing the Indian map into rectangular units of size 0.4 $\times$ 0.4 degrees. A grid is bigger than a pincode but smaller than a district.Appendix Figure A1 shows the grids for Jaisalmer. We assign a pincode to a grid with maximum overlap and restrict the sample to grids with both high and low-exposure pincodes. Our estimates are identified through within-grid variation in UPI exposure across pincodes.

Our key identification assumption follows the canonical difference-in-differences specification that requires that conditional on district-month fixed effects, treated and control pincodes exhibit parallel trends in the counterfactual in the absence of treatment. While this assumption is fundamentally untestable, we provide support by examining the pre-trends in an event study analysis.

To this end, we introduce indicator variables that identify months in relative event-time interacted with High Exposure$_p$ dummy analogous to the specification in Equation (3):

$$Y_{pd(p)t} = \delta_{gt} + \alpha_{d(p)t} + \theta_p + \beta_\tau \times \sum_\tau \mathbb{1}_\tau \times \text{High Exposure}_p + \epsilon_{pd(p)t} \qquad (4)$$

for pincode p belonging to district $d(p)$ in month t. Observations are also at the pincode-month-year level, and τ is an indicator for each month between October 2015 and January 2019. $Y_{pd(p)t}$ is the sanctioned amount (in ₹million) and accounts. δ_{gt}, $\alpha_{d(p)t}$, and θ_p are district×month, grid × month and pincode fixed effects as in Equation (2). β_τ captures the difference in outcomes for each of the dependent variables between the treatment group and the control group at time τ relative to October 2015.

3 The effect of UPI on credit

The open payment system lets users create and share their financial history with any financial institution, unlike traditional banking, where banks control customer data. By reducing lender-borrower information asymmetry and lowering screening costs for new entrants, open payment systems can potentially expand credit access. In this section, we examine the impact of UPI on credit markets. UPI, a Digital Public Infrastructure, allows users to generate financial transaction data, eliminating the need for incumbents to invest in generating consumer data. While this may disincentivize incumbent banks from generating data, public provision of digital payment infrastructure through UPI sidesteps banks' disincentives.

We analyze credit flow across borrower risk profiles to understand heterogeneity in effects across underserved and served customer segments. Moreover, even with Digital Public Infrastructure, there is reason to expect differential effects for fintechs versus banks. Fintechs adopt technology and data analytics quicker than banks (Buchak et al., 2018; BIS, 2019; Fuster et al., 2019; Seru, 2020; Mishra et al., 2022). The resulting cost savings can enable fintechs to increase credit access and provide consumers with improved convenience. Therefore, the effects of Open Banking on banks and fintechs must be separately analyzed to understand the equilibrium effect in credit markets (Seru, 2020). Figure 3 shows the credit composition in Rupee terms for banks and fintechs across borrower creditworthiness for 2015–2019. Overall, credit increases across the board, but fintechs grow significantly faster over the four years. New-to-credit and subprime loans form a more significant fraction of fintechs' loan portfolio, suggesting market segmentation with fintechs catering to underserved borrowers. As of 2019, approximately 27% (15%) of fintechs' (banks') overall lending is to new-to-credit and subprime borrowers. In the aggregate, fintechs remain a small fraction relative to banks.

The time trends in the number of loans show that while prime loans grew for fintechs, banks exhibited much stronger growth (Figure 4). In contrast, banks exhibited muted growth in the subprime and new-to-credit segments, while fintechs exhibhit a considerable uptick in these underserved segments. The raw plots also suggest that banks and fintech exhibit parallel credit supply trends up until the introduction of UPI.

Temporal dynamics We assess the parallel trends assumption more formally. The identification assumption in our difference-in-differences setup requires that conditional on district-month fixed effects, treated and control pincodes exhibit parallel trends in the counterfactual absent treatment. Since this is a fundamentally untestable assumption, we provide support by examining the pre-trends in an event study analysis. Figure 5 plots the coefficient estimates (β_τ) over time using Equation 4. The dependent variables are loan value and loan volume. Panels A, C, and E (B, D, and F) report the estimates for credit amount (number of loans) for the total (=banks + fintechs), fintechs, and banks, respectively. Each point on the navy-blue line shows the difference-in-differences estimate for each month in the period October 2015-January 2019 relative to the baseline October 2015. The vertical dotted lines denote the 95% confidence intervals around the point estimates. Consistent with parallel pre-treatment trends, we do not observe a statistically significant difference across high- and low-exposure regions in the pre-treatment period in either the amount of credit or the number of loans sanctioned. Post-UPI launch, we observe a differential increase in credit in the treated pincodes.

Difference-in-differences estimates Estimates from the difference-in-differences specification from Equation 3 are shown in Table 3. The dependent variables are total loan value and volume, representing the combined intensive and extensive margin effect across borrower credit risk profiles. The coefficient on the interaction term, High-Exposure×Post, in column 1 shows a ₹4 million differential increase in loan value in high-exposure pincodes, representing a 55% increase relative to the pre-treatment mean. Column 2 shows a 67% increase in the number of loans relative to the pre-treatment mean. To examine the impact on financial inclusion, we focus on the sub-sample of subprime borrowers (columns 3–4) and new-to-credit borrowers (columns 5–6). Credit to subprime borrowers increased by 47% in rupee value terms and by 55% in the number of loans (columns 3–4). The number of loans to new-to-credit borrowers increased by 28%, and 13 % in value (columns

5–6). Since these are first-time borrowers, this increase represents an expansion along the extensive margin. The larger increase in the number relative to the value of loans indicates an increase in small-ticket loans.

Interestingly, credit to prime borrowers increased by 74% in value terms and by 87% in quantity (columns 7–8). UPI decreased the information asymmetry between lenders and borrowers, reducing the cost of customer acquisition. Third-party payment service providers in India, such as Google Pay (GPay), have partnered with banks and enabled digital-only, small-ticket, paperless loans to individuals and merchants on the GPay application with approval and disbursal in real-time. Lenders are able to access a larger pool of customers and reach prime borrowers in smaller towns and villages. Due to the digital nature of loan applications, the borrowers' transaction costs in applying for loans and the banks' cost of offering and servicing smaller ticket loans have gone down.[15] Consistent with this thesis, RBI data indicates that nearly 35% of traditional banks' unsecured digital lending originated on third-party digital platforms such as GPay in 2021. Thus, UPI enabled an expansion of credit small-ticket loans, even for prime borrowers. In contrast to underserved borrowers, where a digitally verifiable income trail enables better credit risk assessment, the increase in credit to prime customers is likely driven by ease and decline in servicing costs due to UPI.

Post-UPI adoption, incumbents such as banks could have reduced incentives to produce soft information, potentially hurting credit supply if fintechs cannot substitute for the soft information production expertise of banks. These competitive frictions can also adversely affect borrowers previously served by banks (Parlour et al., 2022). Open digital payments such as UPI enable credit access for traditionally underserved or historically disadvantaged groups by creating a digital history of income and consumption transactions that can be used to evaluate the credit risk of borrowers, leading to an increase in credit (Parlour et al., 2022). Which of these effects dominates is thus an empirical question. Our results show that aggregate credit increases, including for subprime and new-to-credit borrowers, indicating that the second effect dominates. However, these effects could mask heterogeneity across lenders, especially since technological shifts are likely to affect banks and fintechs differently (Buchak et al., 2018; Seru, 2020). Panels C, D, E, and F of Figure 5 present the dynamic estimates based on Equation (4) for fintech and banks separately. Consistent with the parallel trends assumption, we do not observe a statistically significant difference across high- and low-exposure regions in the pre-treatment period in either credit amount or number of loans.

[15]The average loan size in GPay is under $360 in size, and 80% of these loans have been credited to Indians living in smaller cities and towns. (source: TechCrunch report, Oct 19,2023)

Table 4 reports the average treatment effect estimates using Equation 3. Fintechs' loan amount increases on average by 0.11 million monthly, corresponding to a 56x increase in high-exposure pincodes relative to the pre-period mean (column 1, Panel A). Correspondingly, the number of loans increases by 5.7 (81x). In contrast, bank credit increases by 54% in value terms and 55% in quantity terms (columns 3–4). Panels B and C examine credit to subprime and new-to-credit borrowers, respectively. Fintech credit to subprime borrowers increases by ₹0.01 million, corresponding to a 23x increase (column 1, Panel B). The number of loans increases by 0.52 or 40x (column 2, Panel B). In contrast, bank lending to subprime borrowers increases by a relatively more modest 44% (=0.190/0.436) and 37% (=1.074/2.873), in value and quantity, respectively (columns 3 and 4, Panel B). Effects are similar for new-to-credit borrowers, with an increase of ₹0.018 million (45x) in loan value and 1.4 (83x) new loans for Fintechs (Panel C, columns 1 and 2) but displays relatively modest growth for banks (Panel C, columns 3 and 4).

Overall, these results suggest a segmentation of customers served by fintechs and banks. Fintechs leverage the digital information enabled by UPI and open data sharing to expand access to traditionally underserved customers along both extensive and intensive margins.[16] In contrast, banks leverage Open Banking to access a larger pool of ex-ante-included borrowers and expand credit to prime borrowers. The growth in fintech credit and lack thereof in bank credit to the underserved categories of borrowers also helps allay concerns that the estimated effects are driven by economy-wide changes.

Why don't banks expand credit access to marginal borrowers? Subprime and new-to-credit borrowers typically take smaller loans than prime borrowers, a segment with low-profit margins. To be profitable through small-ticket loans, lenders need to scale up quickly. Further, Fintech lenders can quickly adapt to technological innovations (Buchak et al., 2018; Fuster et al., 2019) in contrast to banks (Mishra et al., 2022). Since Fintechs operate digitally, they need lower capital expenditure to scale up as opposed to traditional banks that have high fixed costs and are slow to adopt new technology. Hence, it may be more profitable for banks to serve prime borrowers who demand larger loans.

Economic magnitudes Our difference-in-differences design measures the effect in high-exposure pincodes relative to the low-exposure pincodes, and hence cannot be aggregated up to the economy-wide level, also known as the "missing intercept" problem. Hence, we benchmark aggregate *growth* numbers. We use total outstanding loans from RBI and calculate the annualized growth in net credit flow (new consumer loans granted minus

[16]These results stand in striking contrast to the US, where fintech lenders leveraged technology to offer convenience and target ex-ante included and more creditworthy borrowers (Buchak et al., 2018; Fuster et al., 2019), with limited expansion overall to underserved households.

consumer loans repaid).[17] The average unconditional annualized economy-wide growth in unsecured consumer loans (personal loans + consumer durables) computed from RBI's data stands at 23.5%. Our treatment effect estimate of a 15% differential increase in high-exposure regions is comparable and both economically meaningful and plausible.

One worry is that the large growth numbers (summarized in Internet Appendix Table IA3) for fintechs and marginal borrowers simply represent a low base effect. To make sense of these estimates, we benchmark against monthly per capita expenditure (MPCE)[18]. Overall, the average size of the fintech loan is ₹25,155(=₹0.162 million/6.44), representing nearly 3.9x (=₹25,155/₹6,459) of urban MPCE and 6.66x (=₹25,155/₹3,773) of rural income. However, fintechs cater to new-to-credit and subprime segments, and hence, MPCE from lower percentile groups may be a more appropriate benchmark. Using the bottom 5$^{\text{th}}$ percentile of MPCE (₹2,001 for urban and ₹1,373 for rural), the fintech lending to new-to-credit borrowers translates to 6.69x of urban MPCE and 9.74x of rural MPCE. Similarly, for subprime credit, this translates to nearly 7.83x and 11.41x of urban and rural MPCE. Average monthly expenditures are a more appropriate benchmark for our setting, given the cyclicality of incomes (especially rural incomes). Nonetheless, we also benchmark against income. Using the average annual income of ₹234,551 and ₹71,163 for the bottom 50$^{\text{th}}$ from Bharti et al. (2024), average fintech loan size translates to 10.7% of average annual income and 35% of the bottom 50$^{\text{th}}$ annual income percentile. Using the average monthly savings of ₹15,625 [19] as a benchmark, these estimates (1.61x) are meaningful and important.

As an additional robustness check, we also compare only neighboring pincode pairs (similar to Beerli et al. (2021)). We include only those low-exposure pincodes in the control group that share a boundary with a high-exposure pincode. Each pincode-neighbor pair is assigned a unique Pair-id and merged with the baseline data. We include Pair-id $\times$ month fixed effects and show results remain robust (Internet Appendix Tables IA7–IA10).

We examine three mechanisms enabling credit access: (i) the consumer consent-driven data-sharing enabled by Open APIs, (ii) the preceding rise in bank account holdings of (previously) financially excluded households, and (iii) the rapid geographic expansion of 4G networks with high speed and low data costs. Finally, using loan-level data, we more directly link UPI transactions to lenders' credit assessment.

[17] There is no publicly available data source on new loan originations. Hence, we rely on data on loans outstanding from RBI's aggregate statistics.

[18] Data for MPCE is from Household Consumption Expenditure Survey Data from the Ministry of Statistics and Program Implementation, Government of India website.

[19] Data as of 2019 is from All India Debt and Investment Survey (AIDIS).

3.1 Open API as a mechanism

In traditional financial systems, incumbents such as banks retain control over consumers' financial data, which gives them a competitive edge but can also limit competition and innovation. While open data sharing can boost competition, innovation, and credit access, it can also inadvertently reduce credit access if incumbents become reluctant to invest in generating consumer data they do not own (Parlour et al., 2022; He et al., 2023). Cross-platform public digital payments infrastructure, such as UPI, addresses incumbents, such as banks' disincentives in generating digital data. Thus, a digital payment infrastructure that enables the creation of a digitally verifiable financial history, in conjunction with consumer consent-driven open data-sharing arrangements, can potentially help expand credit access. However, it remains an open question whether mandated open-data sharing can expand credit access.

We use the introduction of "Open Application Programming Interfaces" (Open APIs) in early 2018 by the Reserve Bank of India–a key step in strengthening the digital public architecture in India to examine whether and how the provision of a public digital payment infrastructure, combined with open-data sharing infrastructure, affects credit access. Open APIs enabled the seamless and instantaneous sharing of customer financial data across financial intermediaries, allowing new entrants (fintechs) to access customer payment data for credit underwriting. Formally, Open APIs are a set of standardized rules and tools that enable different financial institutions to securely and efficiently exchange customer permissioned data such as payments and transaction histories—with explicit customer consent. Banks adopted this Open API setup in a voluntary and staggered manner. We exploit this to construct a time-varying API Exposure measure, defined as

$$\text{API Exposure}_{pt} = \frac{\text{Total deposits of API Adopter Banks}_{pt}}{\text{Total Deposits of all Banks}_{p}} \tag{5}$$

This measure is similar in spirit to UPI Exposure, except that it is continuous and time-varying. We then study the differential impact of API Exposure in High UPI Exposure pincodes, on credit outcomes, using the following triple-differences specification

$$\begin{aligned} Y_{pd(d)t} =& \alpha_{d(p)t} + \delta_{gt} + \theta_p + \gamma \times \text{API Exposure}_{pt} + \beta \times \text{Post}_t \times \text{High Exposure}_p + \\ & \kappa \times \text{API Exposure}_{pt} + \text{High Exposure}_p + \epsilon_{pd(p)t} \end{aligned} \tag{6}$$

for pincode p belonging to district $d(p)$ in month-year t. Other variables are defined in Equation 3. κ captures the incremental impact of API Exposure in High Exposure pincodes, relative to low exposure pincodes.

Table 5 presents the results. Pincodes with high UPI exposure and increased exposure to Open API see higher overall credit access, relative to pincodes with low - UPI exposure (column 1-2). Similar results are seen for subprime, new-to-credit, and prime loans (columns 3-8), indicating that the Open API was critical in facilitating credit access across the board. While UPI has an independent positive effect on credit expansion, Open API amplifies this effect manifolds. The increase in credit to pincodes with greater exposure to both UPI and Open API is 200% more than that for pincodes with high UPI exposure but low Open API exposure.

These results show that credit expansion—particularly to subprime and new-to-credit borrowers—is strongest in areas with high UPI and high API exposure, underscoring the complementarity between digital payments and open data-sharing infrastructure. In contrast, Open APIs alone, without a digital transaction trail, show no significant effect. This highlights the strong complementarity between digital payments and open-data sharing infrastructure. Without a digital payment infrastructure like UPI, Open API has no effect as borrowers have a limited digital trail to share.

3.2 Financial formalization

Customers need a bank account to use UPI. A previous large-scale universal banking program, JDY, dramatically increased households' access to bank accounts in previously financially excluded regions. We examine whether access to JDY accounts and UPI together enabled credit access to underserved borrowers using the specification:

$$\begin{aligned} Y_{pd(p)t} =& \alpha_{d(p)t} + \delta_{gt} + \theta_p + \beta \times \text{Post}_t \times \text{High Exposure}_p + \gamma \times \text{High JDY}_p \times \text{High Exposure}_p \\ &+ \eta \times \text{Post}_t \times \text{High Exposure}_p \times \text{High JDY}_p + \epsilon_{pd(p)t} \end{aligned} \tag{7}$$

for pincode p belonging to district $d(p)$ in month-year t. High JDY_p is one for pincodes in the top tercile based on the total number of JDY account openings as of November 2016. Other variables are defined in Equation 3. η measures the differential impact on credit in high-exposure pincodes with a greater number of JDY account holders relative to low-exposure pincodes with a smaller number of JDY account holders.

Table 6 presents the results. Credit increase in high-exposure pincodes is differentially higher in pincodes with high penetration of JDY accounts relative to high-exposure pincodes with fewer JDY accounts (columns 1–2). In columns 3 and 4, we restrict attention to fintech loans. These results are qualitatively similar. Finally, consistent with our hypothesis that JDY enabled new-to-credit borrowers to access credit, columns 5–6 indicate a sharper differential increase in loan value and the number of new-to-credit loans in high-exposure pincodes with a greater number of JDY account holders.[20]

These tests further strengthen the thesis that the cross-platform open payments infrastructure enabled underserved and unserved borrowers to access the credit market, contrary to developed countries where fintech increased lending to borrowers previously served by traditional banks (Buchak et al., 2018). Even within high-exposure pincodes, treatment effects are higher in regions with a greater number of JDY account holders. The higher credit growth in ex-ante underserved markets is unlikely to be driven by other confounding factors that differentially impact high-exposure pincodes. These results highlight the complementarity between bank accounts for the unbanked and digital payment infrastructure with open data-sharing arrangements in expanding credit access.

3.3 Connectivity to low-cost high-speed internet

Given the role of new technology and alternate data in credit risk evaluation, digital inclusion complements banking technology in expanding financial inclusion (Berg et al., 2020). UPI use requires access to fast, reliable, and low-cost internet. To examine this idea, we use the rapid expansion of Reliance Jio (Figure 6, Panel A), which launched 4G services in September 2016, as an experimental setting. Our empirical design exploits the proximity of pincodes to a Jio Tower as a source of exogenous variation in cheap and reliable internet access. The average distance to a 4G tower decreased from 15.1 km in 2016 to 2.1 km in 2020. Costs of internet usage went down dramatically, and the price of 1 GB of data fell from ₹228 in 2015 to ₹9 in 2020 (Panel B). The digital gap across regions also narrowed as Jio's 4G network coverage expanded (Panel C). Formally, to estimate the effect of complementarity between UPI exposure and proximity to a Jio tower, we use the specification:

$$\begin{aligned} Y_{pd(p)t} = &\delta_{gt} + \alpha_{d(p)t} + \theta_p + \gamma \times \text{Early}_{\text{Jio}} \times \text{Post}_t + \chi \times \text{High UPI Exposure}_p \times \text{Post}_t + \\ &\eta \times \text{Early}_{\text{Jio}} \times \text{High Exposure}_p \times \text{Post}_t + \epsilon_{pd(p)t} \end{aligned} \tag{8}$$

for pincode p belonging to district $d(p)$ in month-year t. Observations are at the pincode-month level and span October 2015 to January 2019. $\text{Early}_{\text{Jio}}$ identifies pincodes that

[20]For ease of interpretation, we also re-estimate our baseline difference-in-differences regression Equation 3 separately for the high- and low-JDY subsamples. Results are in line with Internet Appendix Table 6 and Internet Appendix Table IA11.

received a Jio tower within 6 km by 2017 Q1.[21] Other variables are as defined in Equation 3.

Since we exploit variation in the timing of Jio entry across pincodes, one concern could be that the entry decision is correlated with time-varying factors related to our variables of interest and credit outcomes. To mitigate these concerns, we first examine ex-ante differences in economic activity and credit across the late and early adopter pincodes in balance tests presented in Panel A, Appendix Table A4. Although the early adopter pincodes had higher levels of credit and nightlights per capita, growth trends matter to us. Reassuringly, Jio entered areas with lower credit and nightlight growth first. Jio's entry decision is likely not random. However, since Jio entered areas with lower credit growth first, this biases the estimates against finding a significant effect.

Second, in Panel B, we examine the cross-sectional correlates of Jio entry. These tests allow us to examine the relationship between the entry timing of Jio tower and pincode level credit and economic activity. Jio entry is negatively related to credit growth at the pincode level, suggesting that Jio entered pincodes experiencing faster credit growth later. If anything, this is likely to bias our estimates downward. Importantly, the entry of Jio is uncorrelated with growth in economic activity (proxied using nightlights) and UPI exposure. Moreover, given the low R-squares, these predictors are not quantitatively important in determining Jio entry decision. Most of the variation in Jio's entry into a pincode remains unexplained by credit or economic activity at the pincode level.[22]

Finally, we control for district-specific time-varying aggregate shocks using District-FEs in our regressions. Thus, any potential district-level time-varying factor correlated with Jio's entry is controlled. Further, the event study plots for the early adopter versus late adopter pincodes and confirm that early and late Jio pincodes were trending similarly in the pre-period (Figure 7). Together, these tests help allay concerns regarding the endogeneity of Jio's entry decision, confounding our estimates.

As a precursor to the credit analysis, Internet Appendix Table IA12 confirms that early Jio pincodes indeed have higher UPI transactions. Table IA14 reports the results for the impact on credit. Fintech lending increases in credit in high exposure pincode are driven by the early Jio adopter regions (Panel A). In terms of economic magnitude, low-cost 4G access corresponds to a 20x increase in terms of value and a 49x increase in the credit volume (columns 1–2). Effects are similar for the new-to-credit borrowers (columns 3–4), with a 13x increase in value and a 54x increase in the volume of credit. This important

[21] A tower provides reliable internet access within a 6 km radius.

[22] See Acemoglu et al. (2004) and Hoynes et al. (2016) who make a similar argument based on low R-squares as supporting evidence for exogeneity of the decision to place in an area.

heterogeneity highlights the strong complementarity in payment technology and low costs, enabling reliable internet access. The coefficient on the interaction between UPI exposure and post is insignificant, implying the limited baseline effect of UPI exposure on credit for areas that were late to receive Jio towers.[23]

Our thesis is that Jio brought down the cost of the Internet, expanding credit access among marginal borrowers. However, one could argue that coefficient estimates capture the direct effect of internet access rather than the cost of access. Two observations counter this claim. First, the coefficient on the interaction term for exposure and Post shows that UPI did not affect credit access in areas where Jio entered late. In addition, we restrict to the subsample of late-Jio pincodes and confirm that the effects are primarily driven by the early adopter pincodes (Internet Appendix Table IA13). Since most of the early adopter areas were already covered by non-Jio towers, these results show that the cost of access primarily drives the credit effects. A related concern here is that pincodes with early and late access to 4G may experience other contemporaneous economic shocks.

To further address these concerns, we also obtained data on the location of non-Jio mobile towers.[24] Our event study figures and balance tests comparing early vs. late JIO pincodes help address these concerns to a large extent. Nonetheless, we restrict our sample to pincodes with early access to a non-Jio tower, that is, we hold access to 4g constant, and repeat these tests.[25] These results are reported in Table IA14 of the appendix and remain robust. Overall, these results suggest that low-cost, high-speed internet serves as a catalyst for financial inclusion (D'Andrea and Limodio, 2024).

3.4 Digital verifiability of revenues

Finally, we establish the direct link between UPI transactions and loan disbursement by supplementing our main tests with loan-level data on all loans to roadside kiosk owners for 2020-2023 from a large fintech lender. These tests also serve as an independent test of the external validity of our findings. This lender specializes in lending to small and micro enterprises, tracking all QR-code-based UPI transactions done by the kiosk using the lender's payment app. For each borrower, we obtain data on the value and frequency of UPI transactions, the sanctioned loan amount, the loan interest rate, and the internal credit score estimated by the lender's proprietary algorithm. Only a subset of

[23]For ease of interpretation, we also re-estimate our baseline difference-in-differences regression Equation 3 separately for the early- and late-Jio subsamples. These results are in line with Table IA12 and reported in Table IA13 in the appendix.

[24]Non-jio operators comprise other major mobile telephony providers in India. Non-Jio operators did not immediately lower costs but did increase internet speed through their 4g offering.

[25]For robustness, we repeat these tests with all pincodes. and find qualitatively similar results.

the borrowers are assigned an internal credit score by the lender. Data spans the period 2020–2023. We examine the link between an individual's UPI transactions and credit outcomes using the specification:

$$Y_{it} = \alpha_{s(i)t} + \beta \times X + \epsilon_{it} \tag{9}$$

for a merchant i belonging to a pincode $p(i)$ and state $s(i)$ in month t. Y_{it} takes the following values: loan amount sanctioned, the interest rate, a dummy for whether the lender assigned a borrower an internal credit score, and the lender's internal credit score. X takes the following values: Log of QR-UPI Transaction count$_{it}$ and Log of QR-UPI Transaction Values$_{it}$. $\alpha_{s(i)t}$ are state-time fixed effects. Standard errors are clustered by pincode.

Table 8 presents the results. The descriptive statistics in Panel A suggest a similar, though slightly lower, mean exposure of 0.47 relative to the baseline exposure mean of 0.49. Panel B, columns 1–4, show that the value and frequency of a kiosk's UPI transactions positively correlate with the loan size and negatively correlate with the interest rate. A smaller sample of these borrowers is also assigned an internal credit score by the lender. In columns 5–6, we examine whether the value and frequency of a kiosk's UPI transactions are associated with the likelihood of having an internal credit score. A one percent increase in the value or frequency of transactions is also positively associated with a one percent higher likelihood of being assigned an internal credit score. Finally, in columns 6–8, we restrict attention to the sample of borrowers with an internal credit score and again find a positive correlation between UPI transactions and credit score.[26] Overall, these results are consistent with the idea that lenders are incorporating a digital income trail created by UPI in their credit decisions.

4 Additional tests

4.1 Impact on default

Does the greater access to loans translate to higher default rates? We note that, by design, marginal borrowers are likely to be riskier. So, an increase in credit to such borrowers would naturally lead to an increase in default rates. Thus, UPI, by virtue of expanding credit to underserved segments, should result in higher aggregate defaults. However, our interest is in understanding whether the UPI-led increase in credit leads to higher

[26] For robustness, in Internet Appendix Table IA15 in the Appendix, we repeat the tests in columns 1–4 only for the subsample of borrowers with an internal credit score. The results remain robust.

default rates compared to the old credit approval technology, holding the borrower risk characteristics constant. To test this idea, we compare the default rates on loans made within a specific credit risk category (NTC, Subprime, and Prime) across regions that are more and less exposed to the new UPI technology.

Panel A of Table 9 reports the aggregate univariate statistics on default rates. First, we note that, consistent with an increase in credit to marginal borrowers, default rates rise post-UPI. However, despite the relatively larger increase in credit to marginal borrowers, we find no statistically significant differential increase in default rates in high-exposure pincodes compared to low-exposure pincodes (column 7). One exception is the slightly higher default rates of prime borrowers for fintechs in the aggregate, though the effect disappears once we use our preferred regression specification in Panel B, Table 9, which controls for local effects or time-varying factors. Again, consistent with the univariate analysis, we find no statistically distinguishable effect on default rates overall for either fintech or banks. Interestingly, default rates for subprime borrowers are 3.8% lower, underscoring the fact that fintechs are able to better use alternate data through UPI to cater to marginal borrowers. These results show that digital payment data can enable lenders to lend to underserved, creditworthy borrowers without taking on additional default risk.

4.2 Is demonetization a confounder?

In November 2016, the Indian government announced demonetization that made 86% of the cash in circulation illegal tender. This coincides with the launch of UPI (Chodorow-Reich et al., 2020), raising the concern that our results are driven by demonetization and not due to UPI. Demonetization can affect credit in two ways. Cash shortage induced by demonetization could have led to greater UPI adoption (Crouzet et al., 2023), increasing credit access. This thesis is consistent with our findings, with the intensity of cash shortage being another source of variation in UPI adoption. However, other effects of demonization could also explain the credit uptake: demonetization increased the deposits in the banking sector, relaxing banks' liquidity constraints, resulting in an increase in bank lending (Chanda and Cook, 2022). While plausible, these effects were not sustained over the longer term as depositors pulled out deposits in search of yields post-demonetization due to a drop in banks' deposit rates (Subramanian and Felman, 2019). Further, it is not obvious why the flow of deposits to banks should increase fintech credit to new-to-credit segments. In addition, we find continued increase in credit well after demonetization ended. These temporal credit dynamics cannot be explained by demonetization but can be attributed to better transaction history available to lenders post-September 2017.

Importantly, all our baseline specifications (Equation 3) control for granular grid-by-month fixed effects. This ensures that we are comparing pincodes within very narrow geographies, thus, controlling for demonetization-induced cash shortages that depended on factors such as the distance to the nearest currency printing mints (Crouzet et al., 2023). Mints first distribute their printed currency to currency chests nationwide (designated bank branches), which then send out the cash to nearby branches across banks. Hence, proximity to currency chests was a strong determinant of cash availability during demonetization.

Nonetheless, for robustness, we provide additional evidence to rule out these concerns of possible confounders. We obtain data on the distance to the nearest currency chest (Chodorow-Reich et al., 2020). Reassuringly, the distance to currency chests is uncorrelated with our exposure measure, implying that our baseline UPI exposure measure captures UPI variation orthogonal to the demonetization-induced UPI uptake. In addition, in Appendix Table A5, we repeat our baseline analysis after controlling for the interaction between a pincode's distance from the currency chest and with year-month dummies. These dummies control for any time-varying changes in economic outcomes correlated with the intensity of the demonetization shock/cash shortage, which also impacts credit. Results remain qualitatively unchanged, helping allay concerns that the demonetization episode drives our results, further strengthening the causal interpretation of our findings.

5 Conclusion

Nearly 850 million individuals in India are credit unserved or underserved. A first-order question in financial inclusion is: how do we expand credit access to the marginal population? This paper investigates whether the provision of cross-platform digital payments infrastructure can foster credit access. We employ a difference-in-differences empirical design that exploits regional variation in exposure to the UPI launched in India in 2016. Using unique and rarely available data on the universe of consumer loans, we document a significant increase in credit availability, along both intensive and extensive margins, especially benefiting subprime and new-to-credit borrowers. Both fintech lenders and traditional banks expand credit, albeit targeting distinct borrower segments: fintech firms predominantly serve marginal, previously underserved consumers, whereas banks primarily expand services among prime borrowers.

We show several mechanisms at play. First, our findings underscore the complementarity between digital payments and open data-sharing infrastructure in expanding credit access. Fintech lenders, in particular, capitalized on the digital transaction data generated by UPI and open data sharing to assess creditworthiness and expand access to credit for the traditionally underserved segments. Second, fintech loans to new-to-credit borrowers are higher in regions with ex-ante more new-to-banking customers with no/thin credit history. UPI complements the savings bank account-oriented financial inclusion program (JDY) in expanding credit access. Third, we highlight the complementarity between digital inclusion in the form of low-cost internet and digital payments in increasing credit to marginal borrowers. Finally, using loan-level data from a large fintech lender for roadside kiosk owners, we show that lenders weigh in digital payment histories in their credit approval decisions.

The results of this study inform not just academicians but also help move the debate forward with policymakers. There is much debate about new forms of financial intermediation, the role that governments should take in setting up associated technology-related infrastructure and whether it expands financial access. Given the success of the public provision of digital payments, bank accounts for the poor, and Open API enabled data-sharing infrastructure in providing access to credit, the next question would be if partial movement towards these, e.g., private digital payments, with limited data sharing as proposed in many countries, would still have aggregate effects. These are important questions for further research.

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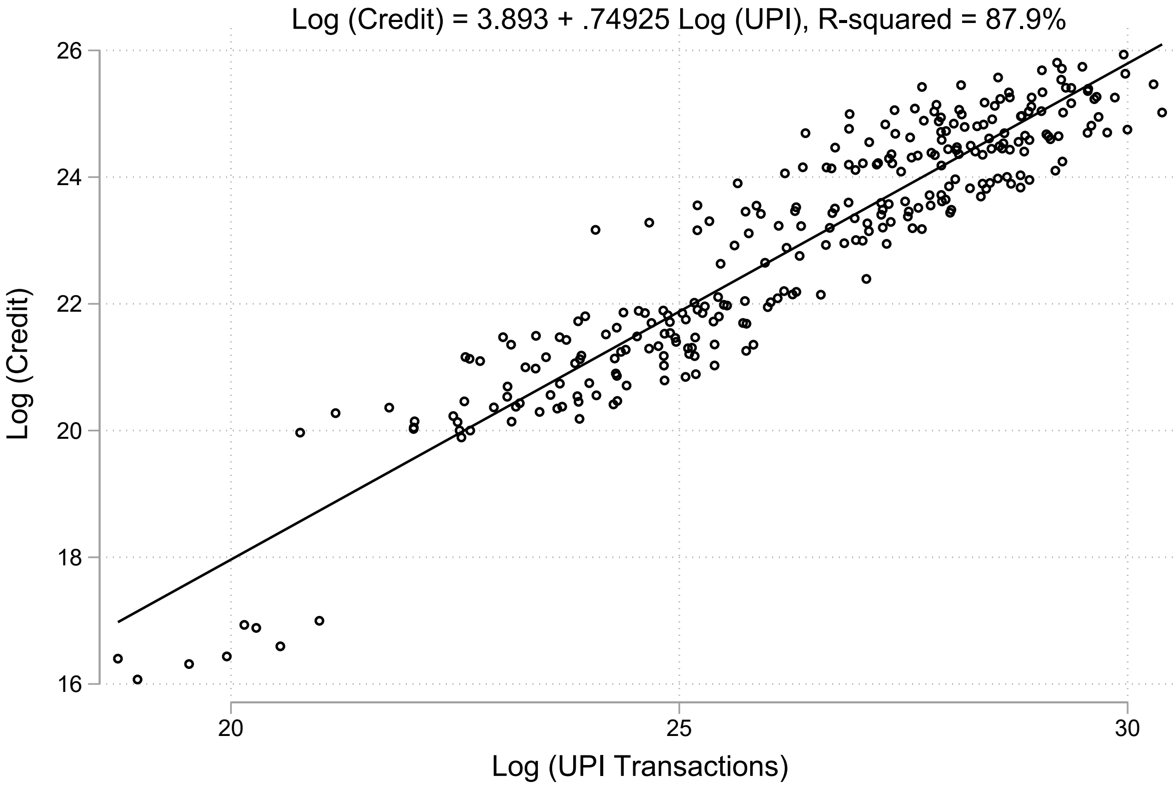
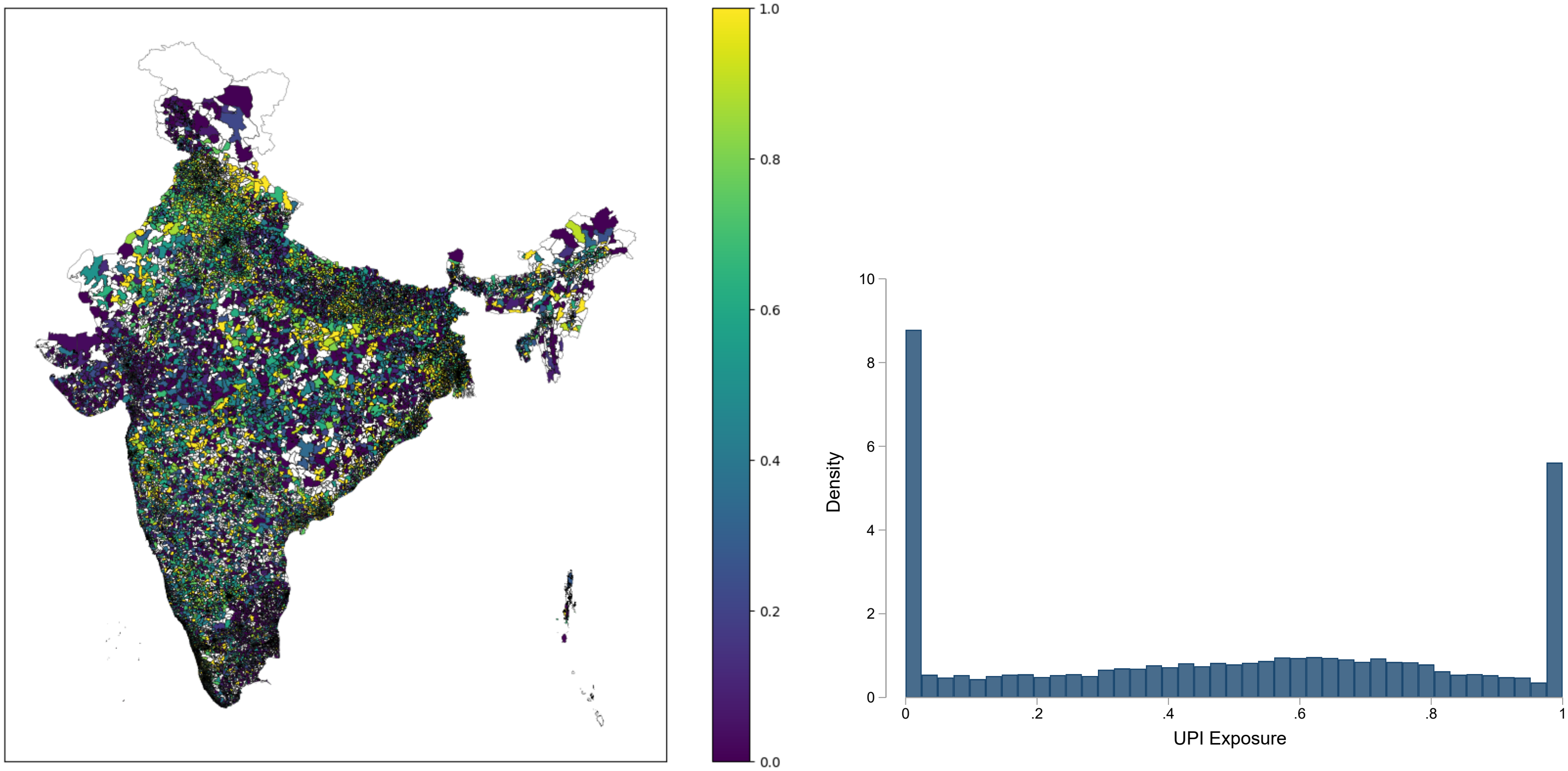
Figure 1
Aggregate Relationship Between UPI and Credit



Notes: This figure shows the cross-sectional relationship between the log of UPI transactions (x-axis) and log credit (y-axis). The data covers the period January 2017 - January 2019, with each dot representing a state-quarter observation. The black line is the line of best fit. The text above the graph shows the estimated regression specification for the line of best fit.

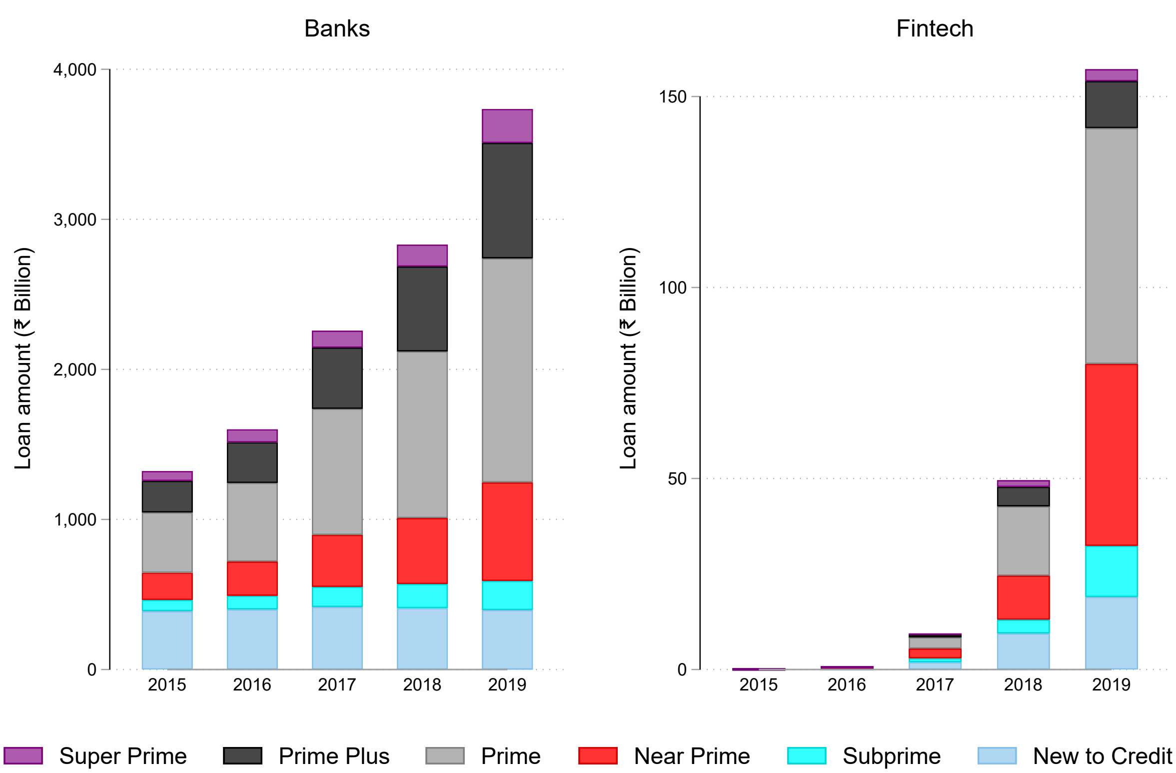
Figure 2
Variation in UPI Exposure



Panel A: Variation across pincode **Panel B: Distribution of exposure measure**

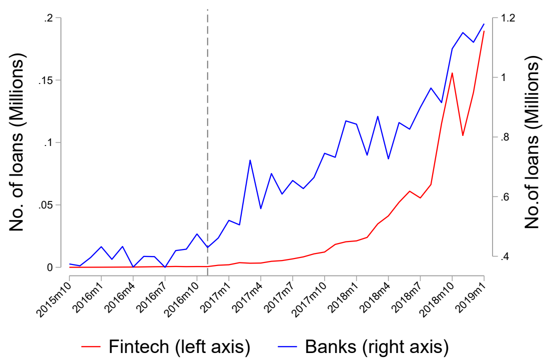
Notes: This figure shows the variation in value of UPI exposure across pincodes. Exposure measure is defined as the ratio of deposits for early adopter banks to total deposits as defined in Equation (1). UPI Exposure is bounded between 0 and 1. Panel A shows the variation on a map, with darker shades corresponding to higher levels of UPI exposure. Panel B shows the same information as a histogram. The classification of early adopter banks is based on information provided by Government of India and as of Q3 2016. Deposit data is from Basic Statistical Returns (BSR) provided by the Reserve Bank of India.

Figure 3
Credit Composition by Lender

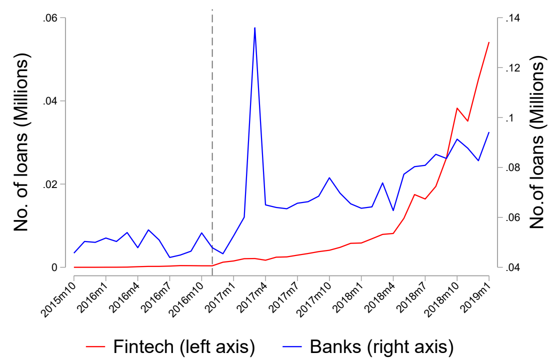


Notes: This figure shows the trends and composition of loan value (₹billion) by Banks and Fintechs, respectively. For each of these lenders, each stacked colored bar represents the credit score band, ranging from Super Prime at the top to New to Credit at the bottom. The trends cover the period 2015-2019.

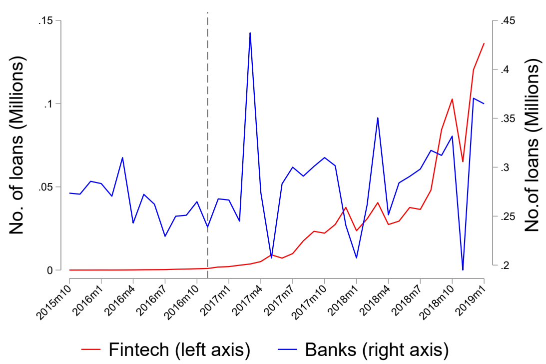
Figure 4
Trends in Credit by Lender



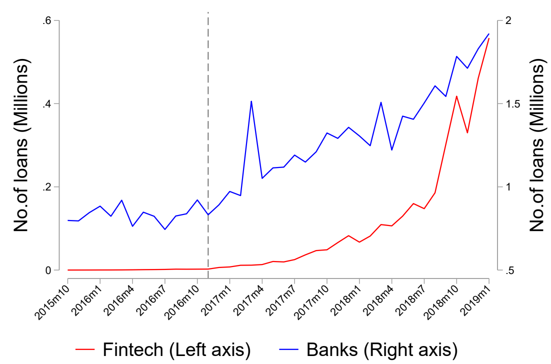
Panel A: Prime



Panel B: Subprime



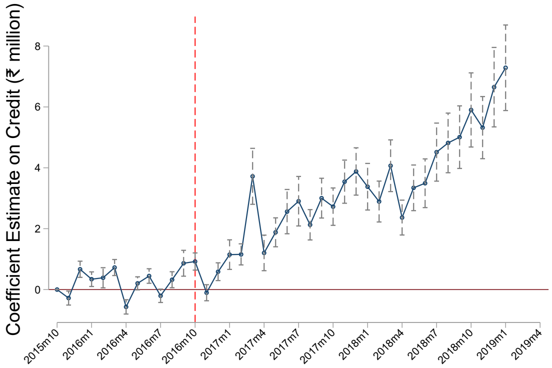
Panel C: New-to-credit



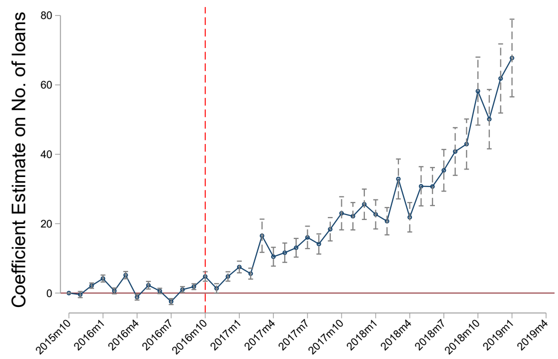
Panel D: All

Notes: This figure shows the number of loans made by Banks (blue line) and Fintechs (red line). For each of these lenders, the trends are shown for Prime (Panels A), Subprime (Panel B), New-to-credit (Panel C) and All (Panel D) credit score bands. The data is at monthly frequency and covers the period October 2015 to January 2019. The dashed vertical line marks the demonetization month (November 2016).

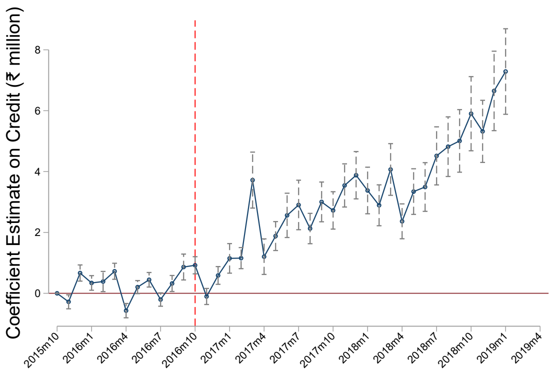
Figure 5
Treatment Dynamics: Impact on Credit



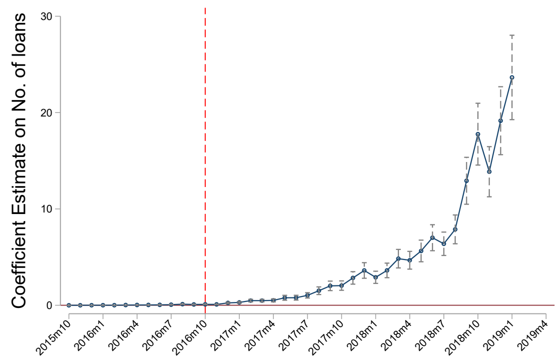
Panel A: Total loan amount



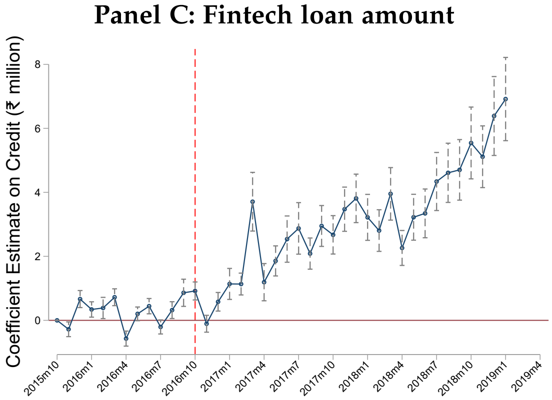
Panel B: Total number of loans



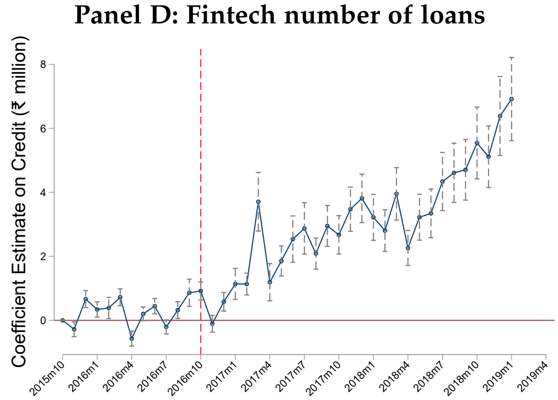
Panel C: Fintech loan amount



Panel D: Fintech number of loans



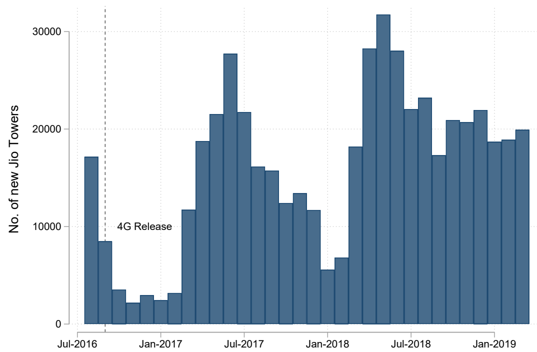
Panel E: Bank loan amount



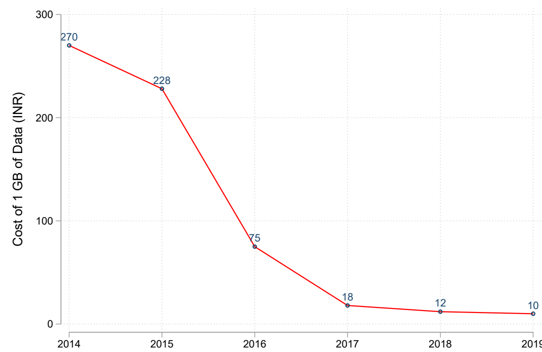
Panel F: Bank number of loans

Notes: This figure shows the treatment dynamics using the specification in Equation (4) for total (Panels A and B), Fintech (Panel C and D) and Bank credit (Panels E and F). The dependent variables are loan value (in ₹million) and number of loans. Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. Each point on the navy line shows the point estimate. The grey dotted lines indicate the 95% confidence intervals. Pincode and district-month-year and grid-month-year fixed effects are included. Standard errors are heteroskedasticity robust and clustered at the pincode level. The dashed red line marks the pre-treatment month (October 2016).

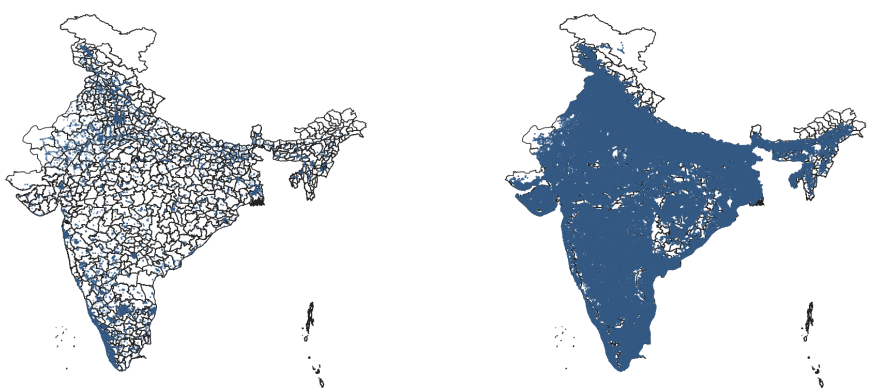
Figure 6
The Jio Revolution



Panel A: New towers



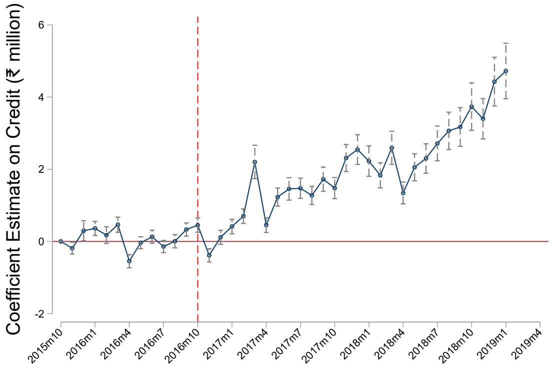
Panel B: Falling data costs

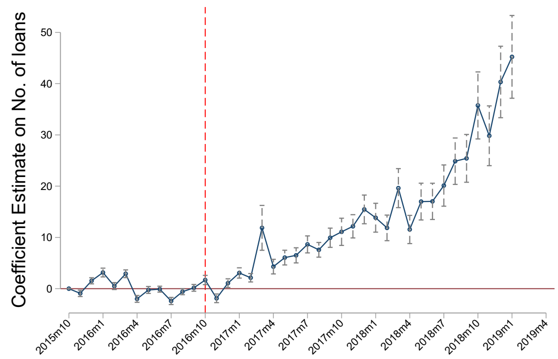


Panel C: Distance to Jio Tower

Notes: This figure shows the rapid growth and accessibility of Reliance Jio as an internet provider. Panel A shows the number of new Jio towers activated every month between August 2016 and March 2019. The dotted line marks September 2016, when 4G internet was activated. Panel B shows the cost of 1 GB of data (in ₹), over the period 2014-2019. Panel C shows the cumulative number of Jio towers in 2016 (left map) versus 2020 (right map). Each blue point represents an active Jio tower.

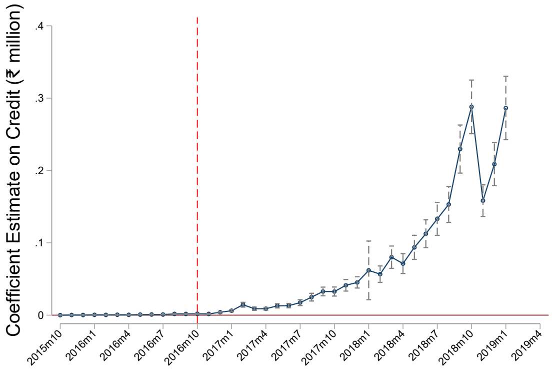
Figure 7
Treatment Dynamics: Impact of Jio

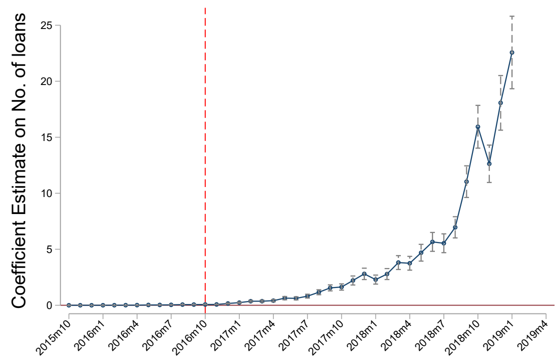




Panel A: Total loan amount

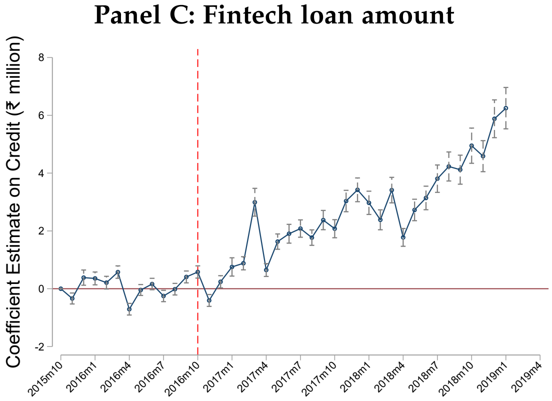
Panel B: Total number of loans

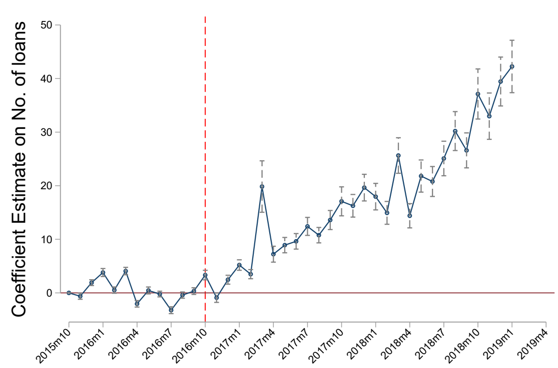




Panel C: Fintech loan amount

Panel D: Fintech number of loans





Panel E: Bank loan amount

Panel F: Bank number of loans

Notes: This figure shows the treatment dynamics estimating the relative effect of Early jio towers ftotal (Panels A and B), Fintech (Panel C and D) and Bank credit (Panels E and F), relative to late Jio towers. The dependent variables are loan value (in ₹million) and number of loans. Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. Each point on the navy line shows the point estimate. The grey dotted lines indicate the 95% confidence intervals. Pincode and district-month-year and grid-month-year fixed effects are included. Standard errors are heteroskedasticity robust and clustered at the pincode level. The dashed red line marks the pre-treatment month (October 2016).

Table 1
Summary Statistics

	Mean	Median	St. Dev
UPI Exposure (N=12,576)	0.49	0.47	0.36
UPI			
UPI Transactions (Value: Million INR)	8.93	2.13	21.13
UPI Transactions (Volume: 1000s)	3.89	1.07	8.46
Credit			
Total Loan Amount (Million INR)	13.66	3.65	42.49
Total no. of loans	93.29	21.00	315.09
By Scoreband			
Subprime Loan Amount (Million INR)	0.79	0.10	2.50
Subprime no. of loans	5.48	1.00	22.34
New-to-credit Loan Amount (Million INR)	2.51	0.91	6.12
New-to-credit no. of loans	22.48	6.00	66.50
By Lender			
FinTech Loan Amount (Million INR)	0.13	0.00	1.22
FinTech no. of loans	6.44	0.00	50.65
Banks Loan Amount (Million INR)	13.53	3.63	41.79
Banks no. of loans	86.85	20.00	282.36
No. of observations (pincode $\times$ month-year)		510,240	

Notes: This table presents the summary statistics for the pincode-month observations. The table summarizes data for UPI Transactions, Total Credit, and two subsamples of the credit data: by credit score and by lender type. The data covers the time period October 2015 to January 2019.

Table 2
Univariate Difference in the Mean Number of Loans by Exposure

Score Band	Number of loans (#)						
	Low Exposure			High Exposure			DiD
	Pre	Post	Post-Pre (Level)	Pre	Post	Post-Pre (Level)	High-Low
	Panel A: Fintechs						
New-to-credit	0.006	1.402	1.396***	0.029	3.786	3.757***	2.361***
Subprime	0.004	0.459	0.455***	0.021	1.375	1.354***	0.899***
Prime	0.008	1.638	1.630***	0.038	4.817	4.779***	3.149***
	Panel B: Banks						
New-to-credit	11.758	13.124	1.366***	27.5	29.375	1.874***	0.508
Subprime	2.14	3.654	1.514***	5.227	7.18	1.953***	0.439***
Prime	16.746	32.74	15.994***	43.237	82.788	39.551***	23.56***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the mean number of loans granted at the pin code-month level for Fintechs (panel A) and Banks (panel B). High and low exposure identify pincodes with above and below median UPI Exposure as calculated from Equation (1). Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. Pre refers to the period before November 2016 and Post thereafter. Means for the pre- versus post and high versus low-exposure are as indicated. The difference between the post versus pre for low-exposure pincodes is shown in column 3. The difference between the post versus pre for high and low-exposure pincodes is shown in column 6. The difference-in-differences (column 6-column 3) is shown in column 7.

Table 3
Impact on Credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score Band	All		Subprime		NTC		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High UPI Exposure × Post	4.244***	32.258***	0.199***	1.590***	0.253***	4.224***	3.081***	20.612***
	(0.435)	(3.833)	(0.022)	(0.231)	(0.027)	(0.532)	(0.320)	(2.341)
R^2	0.901	0.877	0.813	0.808	0.862	0.894	0.881	0.871
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	7.614	48.383	0.437	2.886	1.907	15.045	4.188	23.764
Post-UPI Mean	15.614	109.578	0.890	6.371	2.499	24.019	9.806	61.718
Dep. var mean	13.014	89.690	0.742	5.238	2.307	21.103	7.980	49.383
N	501040	501040	501040	501040	501040	501040	501040	501040

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the impact of UPI exposure on overall, subprime, new-to-credit, and prime loans. Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. The dependent variable in columns 1,3, 5, and 7 is the value of all loans in ₹million, and the dependent variable in columns 2,4,6 and 8 is the number of unique loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 4
Impact on Credit by Lender

	(1)	(2)	(3)	(4)
Lender	Fintechs		Banks	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act
	Panel A: Full sample			
High UPI Exposure × Post	0.112***	5.576***	4.133***	26.707***
	(0.018)	(0.974)	(0.420)	(2.988)
R^2	0.455	0.522	0.903	0.905
Pre-UPI Mean	0.002	0.069	7.612	48.314
Post-UPI Mean	0.192	9.726	15.424	99.936
Dep. var mean	0.130	6.588	12.885	83.159
	Panel B: Subprime sample			
High UPI Exposure × Post	0.009***	0.518***	0.190***	1.074***
	(0.002)	(0.099)	(0.021)	(0.141)
R^2	0.530	0.526	0.811	0.822
Pre-UPI Mean	0.000	0.013	0.436	2.873
Post-UPI Mean	0.015	0.939	0.874	5.440
Dep. var mean	0.010	0.638	0.732	4.606
	Panel C: New-to-credit sample			
High UPI Exposure × Post	0.018***	1.415***	0.234***	2.812***
	(0.003)	(0.238)	(0.026)	(0.338)
R^2	0.579	0.554	0.860	0.906
Pre-UPI Mean	0.000	0.017	1.907	15.028
Post-UPI Mean	0.036	2.647	2.464	21.395
Dep. var mean	0.024	1.792	2.283	19.326
	Panel D: Prime sample			
High UPI Exposure × Post	0.057***	1.945***	3.024***	18.677***
	(0.009)	(0.328)	(0.312)	(2.057)
R^2	0.299	0.518	0.883	0.887
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.023	4.187	23.742
Post-UPI Mean	0.095	3.304	9.712	58.443
Dep. var mean	0.064	2.238	7.917	47.165
N	496640	496640	501040	501040

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the impact of exposure for Fintech lenders on all credit (Panel A), subprime borrowers (Panel B), new-to-credit borrowers (Panel C), and prime borrowers (Panel D). Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. The dependent variable in odd columns is the value of all loans in ₹million. The dependent variable in even columns is the number of loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 5
Mechanism: Open API and data sharing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score Band	All		Subprime		NTC		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
API Exposure × High UPI Exposure	3.682***	38.862***	0.126***	1.969***	0.085***	3.924***	2.893***	24.957***
	(0.437)	(4.673)	(0.024)	(0.286)	(0.030)	(0.538)	(0.354)	(2.911)
API Exposure	-0.076	-4.349	0.026	-0.078	-0.011	-0.265	-0.114	-3.340
	(0.308)	(3.132)	(0.022)	(0.177)	(0.022)	(0.341)	(0.245)	(2.062)
High UPI Exposure × Post	1.966***	13.736***	0.094***	0.596***	-0.063***	0.800***	1.564***	9.771***
	(0.252)	(2.168)	(0.014)	(0.133)	(0.020)	(0.274)	(0.197)	(1.387)
R^2	0.944	0.916	0.849	0.834	0.905	0.935	0.923	0.910
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Dep. var. mean	12.955	88.777	0.745	5.206	2.314	20.949	7.922	48.806
N	463462	463462	463462	463462	463462	463462	463462	463462

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the triple difference estimates for the interacted effect of UPI exposure and API Exposure on overall, subprime, new-to-credit, and prime credit. Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. The dependent variable in columns 1,3, 5, and 7 is the value of all loans in ₹million, and the dependent variable in columns 2,4,6 and 8 is the number of unique loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). API Exposure is a continuous variable, varying at the pincode-month level, as defined in Equation (5). Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 6
Mechanism: Financial Formalization

	(1)	(2)	(3)	(4)	(5)	(6)
Lender	All		FinTech		NTC + FinTech	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act per capita	Amt (Million INR)	Act
High UPI Exposure × High JDY × Post	5.221***	42.748***	0.146***	7.114***	0.025***	1.856***
	(0.651)	(5.376)	(0.023)	(0.983)	(0.003)	(0.256)
High UPI Exposure × Post	0.673*	3.237	0.014	0.769	0.002	0.162
	(0.403)	(3.647)	(0.018)	(0.888)	(0.003)	(0.222)
High JDY × Post	4.502***	33.680***	0.091***	5.092***	0.016***	1.322***
	(0.361)	(3.136)	(0.014)	(0.710)	(0.002)	(0.178)
R^2	0.902	0.878	0.455	0.524	0.580	0.555
Pincode FE	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	7.614	48.383	0.002	0.069	0.000	0.017
Post-UPI Mean	15.614	109.578	0.192	9.726	0.036	2.647
Dep. var mean	13.014	89.690	0.130	6.588	0.024	1.792
N	501040	501040	496640	496640	496640	496640

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the triple difference estimates for the differential impact of UPI exposure on credit in pincodes with high number of Jan Dhan Yojana (JDY) bank accounts, for a sample of all loans (columns 1-2), Fintech loans (columns 3-4), and Fintech loans with new-to-credit scoreband (columns 5-6). Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. The dependent variable in odd columns is the value of all loans in ₹million. The dependent variable in even columns is the number of loans. High JDY is 1 for number of cumulative JDY bank accounts, as of November 2016 lying above the first tercile. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 7
Mechanism: Connectivity With Jio

	(1)	(2)	(3)	(4)
Sample	All		New-to-credit	
Dependent var.	Amt (₹million)	Act	Amt (₹million)	Act
	Panel A: Fintechs			
$\text{Early}_{\text{Jio}}$ × High UPI Exposure × Post	0.135***	6.071***	0.021***	1.488***
	(0.024)	(1.234)	(0.004)	(0.307)
High Exposure × Post	0.026***	1.684***	0.005***	0.456***
	(0.008)	(0.430)	(0.001)	(0.117)
$\text{Early}_{\text{Jio}}$ × Post	0.007	1.325**	0.004**	0.438***
	(0.011)	(0.576)	(0.002)	(0.146)
R^2	0.455	0.523	0.579	0.554
Pre-UPI Mean	0.002	0.069	0.000	0.017
Post-UPI Mean	0.192	9.726	0.036	2.647
Dep. var mean	0.127	6.444	0.024	1.757
N	496640	496640	496640	496640
	Panel B: Banks			
$\text{Early}_{\text{Jio}}$ × High UPI Exposure × Post	3.144***	21.710***	-0.069**	0.711**
	(0.449)	(3.305)	(0.031)	(0.300)
High Exposure × Post	0.891***	5.093***	-0.029	-0.076
	(0.184)	(1.312)	(0.019)	(0.139)
$\text{Early}_{\text{Jio}}$ × Post	0.752***	4.746***	-0.039**	0.001
	(0.223)	(1.656)	(0.019)	(0.170)
R^2	0.944	0.943	0.907	0.949
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	9.744	61.747	2.511	19.629
Post-UPI Mean	15.424	99.936	2.464	21.395
Dep. var mean	13.533	86.851	2.486	20.723
N	501040	501040	501040	501040

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the triple difference estimates for the impact of UPI exposure on credit in pincodes with early access to a Jio tower, relative to late access in the post period, for a sample of Fintech loans (Panel A) and Banks (Panel B). Columns 1–2 include all loans, while columns 3–4 is the subsample of new-to-credit loans.Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. The dependent variables are value loans in ₹million (columns 1, 3, 6) and the number of loans (columns 2, 4, 6). High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). $\text{Early}_{\text{Jio}}$ takes a value 1 when a pincode's distance to an active 4G Jio tower is less than 6 km, as of Q1 2017. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 8
Digital Verifiability of Revenues: Evidence From a Large Fintech Lender

Panel A: Summary statistics

Variable	Mean	St. Dev.	p25	p50	p75
UPI					
UPI Exposure	0.47	0.34	0.12	0.5	0.85
Credit Variables					
Loan Size (in ₹000's)	109.94	124.07	30.00	70.00	140.00
Interest Rate (in %)	1.97	0.28	1.75	2.00	2.10
QR Transactions					
Log(Amount of QR Txns in a month)(in ₹)	9.78	1.45	9.09	9.92	10.69
Log(Count of QR Txns in a month)(in units)	5.29	1.56	4.45	5.49	6.36
Borrower Variables					
Data Reporting System Score (in units)	15.08	4.56	12.00	15.25	18.75
No Prior Formal Loans Dummy (0 to 1)	0.89	0.31	1.00	1.00	1.00
Repeat Borrower Dummy (0 to 1)	0.38	0.49	0.00	0.00	1.00
N		50,643			

Panel B: Loan-level analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Loan Size (in 000's)		Interest Rate (in %)		Internal Credit Score		Internal Credit Score Dummy	
Log(QR T.Value)	34.695***		-0.023***		1.533***		0.010***	
	(0.871)		(0.001)		(0.033)		(0.001)	
Log(QR T.Count)		27.904***		-0.019***		1.314***		0.011***
		(0.689)		(0.001)		(0.031)		(0.001)
R^2	0.166	0.140	0.106	0.104	0.239	0.224	0.933	0.933
State Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Dep Var Mean	109.516	109.516	1.936	1.936	15.055	15.055	0.479	0.479
N	39602	39602	39602	39602	18973	18973	39602	39602

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the summary statistics for the loan level observations (Panel A) and presents evidence regarding the digital verifiability of revenue through QR-based UPI transactions and credit outcomes using data from a large Fintech lender (Panel B). Panel A summarizes data for UPI Exposure, Credit Level Variables , QR Transaction variables and Borrower variables. The data covers the time period 2020 to 2023. Observations are at the loan level. In Panel B,the dependent variable in columns 1–2 is the lender's loan size in thousands. The dependent variable in columns 3–4 is the interest rate in per cent. The dependent variable in columns 5–6 is the internal credit score dummy that identifies customers who have been assigned an internal credit rating by the fintech lender. QR-UPI T.Value and QR-UPI T.Count are monthly QR-code-based UPI transaction values, and transaction frequency is at the borrower-month of the loan level. Data is for 2020-2023. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 9
Impact on Default

Panel A: Summary statistics

Score Band	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Default Rate						
	Low Exposure			High Exposure			DiD
	Pre	Post	Post-Pre	Pre	Post	Post-Pre	High-Low
Fintechs							
New-to-credit	0.064	0.086	0.022*	0.066	0.086	0.019***	-0.002
Subprime	0.135	0.105	-0.031**	0.13	0.108	-0.022***	0.008
Prime	0.043	0.048	0.005	0.026	0.049	0.023***	0.017**
Banks							
New-to-credit	0.016	0.032	0.016***	0.017	0.033	0.016***	-0.000
Subprime	0.016	0.032	0.016***	0.017	0.033	0.016***	0.001
Prime	0.011	0.026	0.014***	0.011	0.026	0.015***	0.0001

Panel B: Impact on default rates

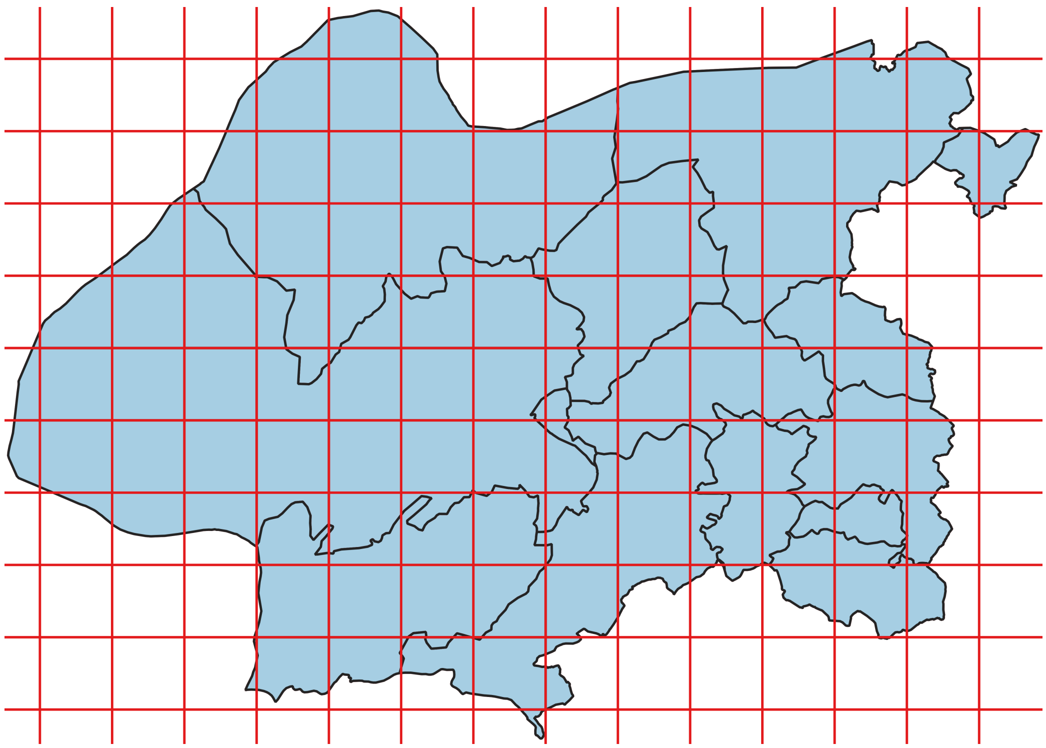
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Default Rate							
Lender	FinTech				Banks			
Score Band	All	Subprime	NTC	Prime	All	Subprime	NTC	Prime
High UPI Exposure× Post	-0.005	-0.038**	-0.006	0.003	-0.000	0.000	0.000	0.000
	(0.010)	(0.019)	(0.033)	(0.012)	(0.000)	(0.001)	(0.002)	(0.000)
R^2	0.359	0.406	0.417	0.385	0.295	0.246	0.317	0.264
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.065	0.056	0.129	0.026	0.017	0.017	0.043	0.011
Post-UPI Mean	0.073	0.086	0.105	0.048	0.032	0.033	0.066	0.026
Dep. var mean	0.072	0.086	0.106	0.048	0.027	0.028	0.060	0.021
N	157822	103363	51495	98334	497073	467526	303829	481700

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the mean default rate at the pincode-month level for Fintechs and Banks (Panel A), and the difference-in-differences estimates for the differential impact of UPI exposure on default (Panel B) . The default rate is defined as the number of defaults divided by total loans in a pincode-month. High and low exposure correspond to dummy variable that identifies pincodes with above/below median exposure, defined as in Equation (1). Data spans the period October 2015 to January 2019. In Panel A, means for the pre- versus post and high versus low-exposure are as indicated. The difference between the post versus pre for low-exposure pincodes is shown in column 3. The difference between the post versus pre for high and low-exposure pincodes is shown in column 6. The difference-in-differences (column 6-column 3) is shown in column 7. In Panel B, Columns 1-4 show results for the subsample of Fintech, and columns 5-8 show results for the subsample of Bank loans. Each column pertains to a score band, namely, all, new-to-credit, Subrpime, and Prime loans. The dependent variable is the default rate. Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Appendix

Figure A1
Grid Example: Jaisalmer



Notes: The figure shows a snapshot of the district of Jaisalmer in the state of Rajasthan India. The black lines demarcate pincodes, denoted by the blue polygons. The red lines denote grids of size 0.4×0.4 degrees.

Table A1
Variable Definitions and Common Terms

Variable	Definition
Unified Payments Interface (UPI)	An instant payment system set up by National Payments Corporation of India (NPCI). It facilitates instant fund transfer between two bank accounts using mobile devices via payment applications.
Banks	Scheduled Commercial Banks comprising public sector banks and private sector banks.
Fintechs	CIBIL classification based on their operational structure.
Prime	Credit score bucket assigned by CIBIL, for borrowers with score in the range 731 and above
Subprime	Credit score bucket assigned by CIBIL, for borrowers with score in the range 300-680
New-to-Credit	Credit score bucket assigned by CIBIL, for borrowers who are taking a loan for the first time, and have no credit score.
UPI Exposure	Total deposits by early UPI adopter banks as a share of total deposits in a pincode for the year 2015.
Jan Dhan Yojana (JDY)	A financial inclusion scheme launched by the Government of India (GoI) in 2014. It aims to provide basic financial services like saving bank accounts, need-based credit, and insurance to financially excluded and weaker sections of society. Services include zero-balance bank accounts, debit cards, and accidental insurance coverage
Reliance Jio	An Indian telecommunications company launched in 2016 and is a provider of 5G, 4G+, and 4G mobile and internet services. It is the largest mobile network operator in the world. It provides multiple internet-related products like Jio 5G sim cards, Jio Fiber broadband internet, Jio cinema OTT platform, and so on.
$\text{Early}_{\text{Jio}}$	A dummy variable taking value 1 if the distance of the nearest Reliance Jio 4G tower from a pincode is less than 6 km, as of 2017 Q1.
$\text{Early}_{\text{Non-Jio}}$	A dummy variable taking value 1 if the distance of the nearest non-Reliance Jio 4G tower from a pincode is less than 6 km, as of 2017 Q1. A non-Reliance Jio tower is defined as the one tower among Airtel, Vi and BSNL 4G towers, which is the closest to the pincode.

Notes: This table defines variables and common terms used in the paper.

Table A2
Balance Tests for Exposure

	(1) High Exposure		(2) Low Exposure		(1)-(2) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Total Credit per capita	6243	819.981 (93.844)	6246	643.127 (67.265)	12489	176.854
Total Credit per capita (Growth)	6242	0.159 (0.003)	6243	0.153 (0.003)	12485	0.007
Subprime + NTC Loan Share per capita	6243	0.000 (0.000)	6246	0.000 (0.000)	12489	-0.000
Subprime + NTC Loan Share per capita (Growth)	6240	0.098 (0.004)	6239	0.105 (0.004)	12479	-0.008
Nightlight Intensity per capita	6243	0.001 (0.000)	6246	0.001 (0.000)	12489	-0.000
Nightlight Intensity per capita (Growth)	6240	0.075 (0.013)	6238	0.077 (0.004)	12478	-0.001

Notes: This table compares ex-ante differences in levels and growth in economic activity and credit across high-exposure and low-exposure pincodes. The variables included are per capita levels and growth of total credit, share of subprime and new-to-credit loans (as a share of total loans), and nightlight intensity.

Table A3
Impact on UPI

Dependent variable	(1) UPI value (₹Million)	(2) UPI volume (in 1000s)
High UPI Exposure	4.353***	1.735***
	(0.329)	(0.135)
R^2	0.489	0.515
District-time FE	Y	Y
Grid-time FE	Y	Y
Dep. var mean	8.967	3.906
N	231975	231975

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the OLS estimates for the impact of exposure on UPI transactions. Observations are at the pincode-month level and span the period January 2017-January 2019. The dependent variables in columns (1) and (2) are the value of all UPI transactions in ₹million and the number of UPI transactions in thousands, respectively. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table A4
Balance Tests for Jio Entry

Panel A: Correlates of Early Jio Entry Pincodes

Variable	(1) Early Jio N	(1) Early Jio Mean/(SE)	(2) Late Jio N	(2) Late Jio Mean/(SE)	(1)-(2) Pairwise t-test N	(1)-(2) Pairwise t-test Mean difference
Credit per capita	7,301	1081.652	5,190	238.632	12,491	843.020***
		(97.212)		(22.758)		
Gwt. credit per capita	7,301	0.127	5,187	0.193	12,488	-0.066***
		(0.003)		(0.004)		
Marginal borr. loan share	7,301	0.000	5,188	0.000	12,489	-0.000
		(0.000)		(0.000)		
Gwt. marg. borr. loan share	7,297	0.087	5,182	0.121	12,479	-0.034***
		(0.003)		(0.005)		
Nightlight per capita	7,301	0.001	5,190	0.000	12,491	0.001***
		(0.000)		(0.000)		
Gwt. nightlight per capita	7,298	0.052	5,182	0.109	12,480	-0.056***
		(0.002)		(0.016)		

Panel B: Determinants of Jio Entry

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Time to Jio entry in a pincode							
Credit growth	0.510***							0.366***
	(0.082)							(0.083)
Marg. borr. credit gwt.		0.461***						0.357***
		(0.067)						(0.066)
Nighlights gwt.			0.001					-0.016
			(0.033)					(0.026)
Credit				0.000				-0.000*
				(0.000)				(0.000)
Marg. borr. credit					3351.685*			10037.054***
					(1972.737)			(3625.300)
Nighlights						26.393**		-38.221
						(11.612)		(42.835)
High Exposure							-0.030	-0.016
							(0.044)	(0.042)
R^2	0.005	0.006	0.000	0.000	0.010	0.005	0.000	0.033
N	11,884	11,878	11,885	11,886	11,886	11,886	11,886	11,877

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Panel A compares ex-ante differences in levels and growth in economic activity and credit across early-jio and late-jio pincodes. Panel B presents the results of cross-sectional regressions examining pre-period predictors of timing of a pincode's entry into Jio 4G. The variables included in both panels are per capita levels and growth of credit, credit to marginal borrowers (subprime and new-to-credit loans) in share of total loans, and nightlight intensity. The dependent variable in Panel B is the time to Jio entry - defined as the number of quarters that a pincode took to first get access to a Jio 4G tower since Q3 2016. Panel B also includes High Exposure dummy that identifies pincodes with above-median exposure, defined as in Equation (1). The credit variables take pre-period (Q3 2015-Q2 2016) mean values, while nightlight intensity (growth and per capita) is the annual mean value calculated across 2014-2016. All the growth variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the district level.

Table A5

Robustness to Demonetization Controls: Impact on Credit

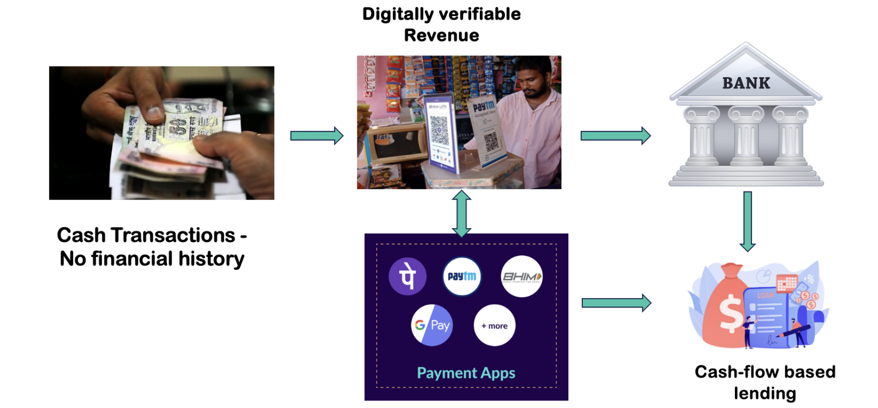
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score Band	All		Subprime		NTC		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High UPI Exposure × Post	4.096***	31.183***	0.190***	1.532***	0.242***	4.071***	2.978***	19.945***
	(0.431)	(3.811)	(0.022)	(0.230)	(0.027)	(0.529)	(0.317)	(2.325)
R^2	0.901	0.877	0.814	0.809	0.862	0.894	0.882	0.871
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y	Y	Y
$Dist_{CC} \times$ Month Control	Y	Y	Y	Y	Y	Y	Y	Y
Dep. var mean	13.014	89.690	0.742	5.238	2.307	21.103	7.980	49.383
N	501040	501040	501040	501040	501040	501040	501040	501040

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the impact of exposure on overall, subprime, new-to-credit and Prime credit. Observations are at the pincode level at monthly frequency for the period October 2015 to January 2019. The dependent variables in odd columns is the value of all loans in ₹million and the dependent variable in the even columns is the number of loans. High exposure is 1 for above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Pincode and Fixed effects are included as indicated. $Dist_{CC} \times$ Month Control is the interaction of the distance of a pincode to the nearest currency chest and month-year t. Pincode clustered standard errors are reported in parantheses.

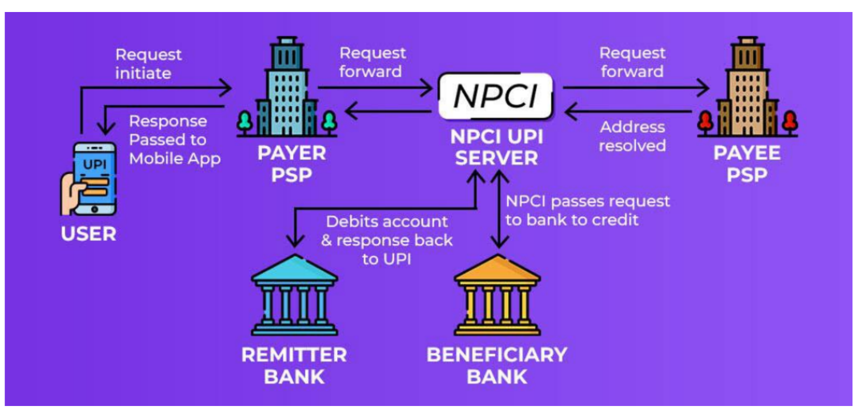
Internet Appendix

Figure IA1
UPI and Credit: Schematic Diagram



*Notes:*This figure is a schematic representation of how the introduction of an open banking digital platform (UPI) leads to an increased disbursal of credit. The leftmost box refers to a pre-open banking stage, where most transactions occur in cash, leading to a lack of documented history. Introducing payment apps based on open banking (bottom middle box) leads to digital verifiability of revenue history. UPI payments are often made through QR codes (top middle box). This information is consequently also available to lenders like banks (top rightmost box), who then use this information to determine creditworthiness and lend based on cash flow (bottom rightmost box).

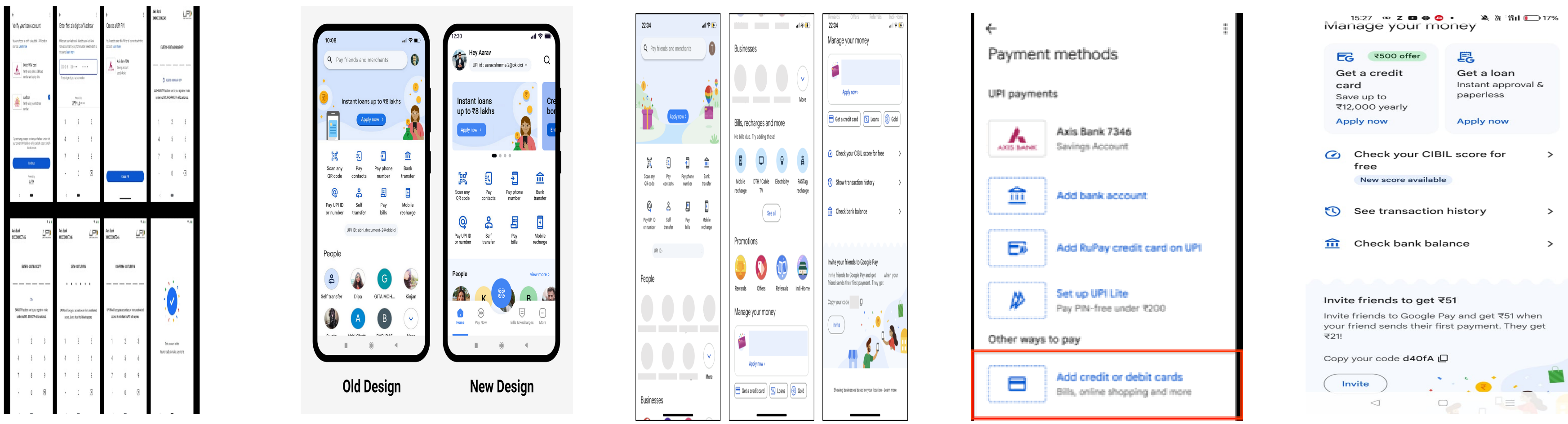
Figure IA2
UPI Payments: Flow Chart



Notes: This figure shows the underlying technical infrastructure for UPI. The remitter and Beneficiary Bank refer to the sender and receiver bank, respectively. Payer and Payee PSP refer to the sender's and receiver's payment service provider. Source: IMF

Figure IA3

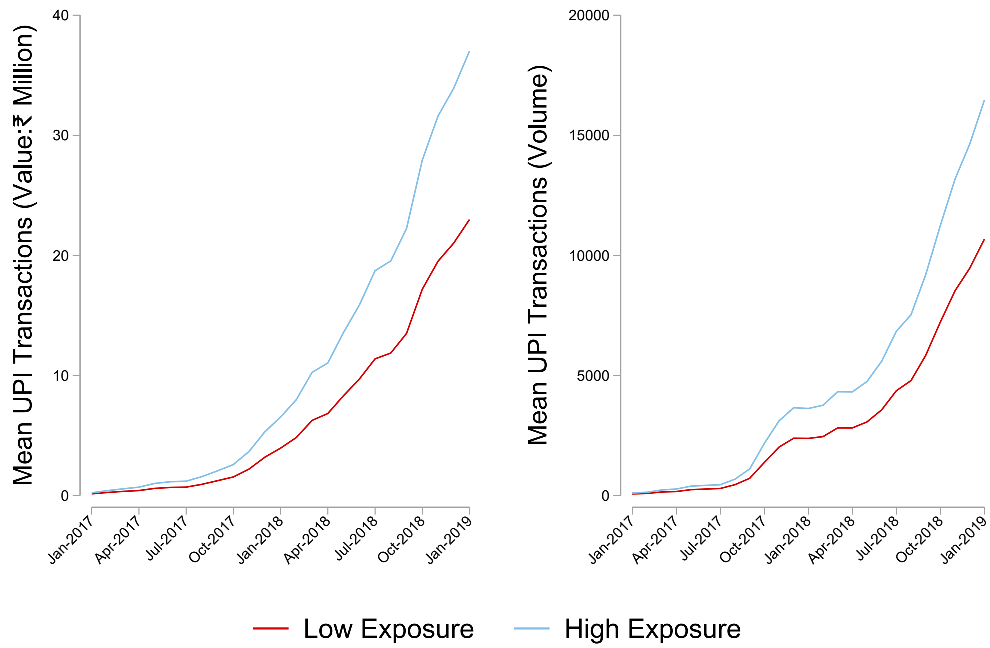
UPI Loan Application Navigation Page



Panel A: Account Opening **Panel B: Landing Page** **Panel C: Google Pay Interface** **Panel D: Payment Method** **Panel E: Loan Application**

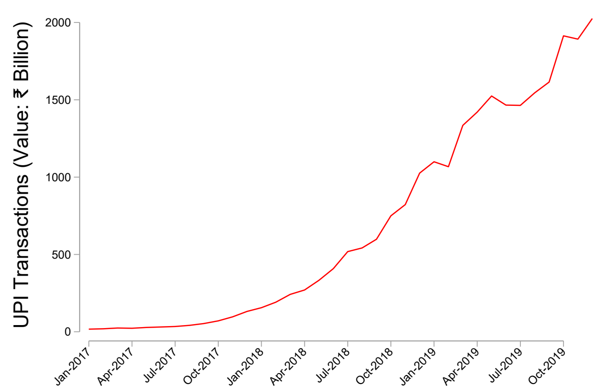
Notes: This figure shows the various stages of navigating UPI as a payment system. It begins with the process of account opening (Panel A), an illustrative landing page (Panel B), the interface of a payment system called Google Pay (Panel C), the various payment methods available (Panel D), and the option to apply for a loan (Panel E).

Figure IA4
Trends in UPI Transactions by Exposure



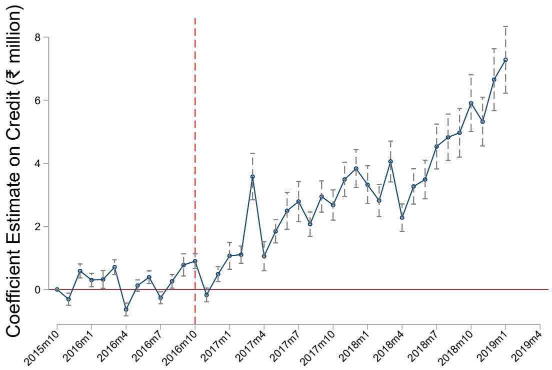
Notes: This figure shows the mean value of UPI Transactions (in ₹million) and mean number of UPI Transactions for low UPI exposure pincodes (red line) and high UPI exposure pincodes (blue line). The data is at a monthly frequency and covers the period January 2017 to January 2019.

Figure IA5
Trends in UPI Transactions

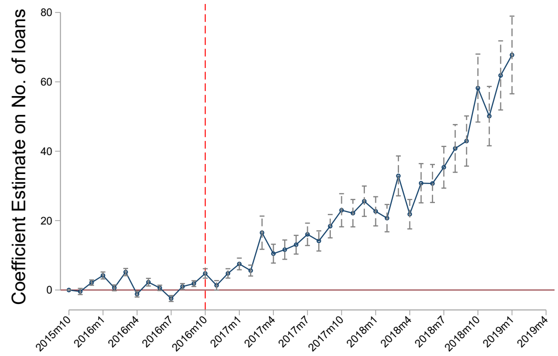


Notes: This figure presents the aggregate trends in the value of UPI transactions over the period January 2017 to December 2019. The unit of transactions is ₹billion.

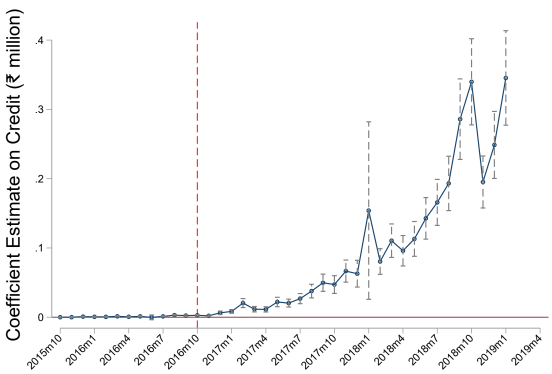
Figure IA6
Robustness Without Grid Fixed Effect: Treatment Dynamics for the Impact on Credit



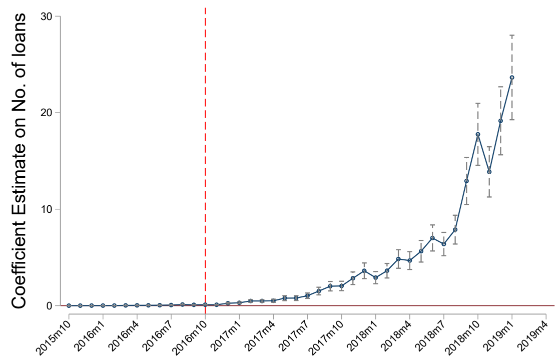
Panel A: Total loan amount



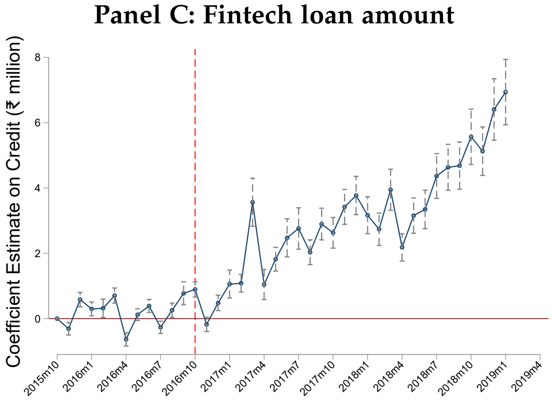
Panel B: Total number of loans



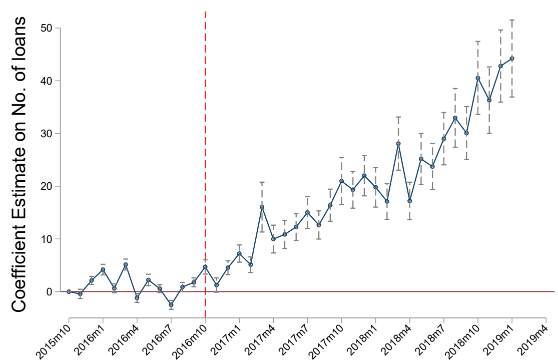
Panel C: Fintech loan amount



Panel D: Fintech number of loans



Panel E: Bank loan amount



Panel F: Bank number of loans

Notes: This figure shows the treatment dynamics using the specification in Equation (4) for total (Panels A and B), Fintech (Panels C and D) and Bank credit (Panels E and F). The dependent variables are loan value (₹million) and number of loans. Underlying observations are at the pincode level at the monthly frequency for the period October 2016 to January 2019. Each point on the navy line shows the point estimate. The grey dotted lines indicate the 95% confidence intervals. Pincode and district-month fixed effects are included. The dashed red line marks the pre-treatment month (October 2016).

Table IA1
Validation of Datasets

	RBI Bank Credit	NPCI UPI Transactions Value	NPCI UPI Transactions Volume
Bank Credit (CIBIL)	0.82	-	-
UPI Transactions (Value: Dataset)	-	0.97	-
UPI Transactions (Volume: Dataset)	-	-	0.97

Notes: This table reports the correlations between credit and UPI data and aggregate statistics on the same available from public sources. RBI reports aggregate data on outstanding consumer loans, while NPCI provides aggregate statistics on UPI transactions. The proprietary credit and UPI transaction data is aggregated at the country level and the correlations with the numbers reported by RBI and NPCI are presented.

Table IA2
Univariate Difference in the Mean Amount of Loans by Exposure

Score Band	Loan Amount (Million INR)						
	Low Exposure			High Exposure			DiD
	Post	Pre	Post-Pre (Level)	Post	Pre	Post-Pre (Level)	High-Low
				Panel A: FinTech			
New-to-credit	0.018	0.001	0.017***	0.052	0.001	0.051***	0.034***
Subprime	0.006	0.000	0.006***	0.023	0.001	0.023***	0.017***
Prime	0.04	0.000	0.040***	0.145	0.002	0.143***	0.104***
				Panel B: Banks			
New-to-credit	1.685	1.659	0.026**	3.262	3.364	-0.102***	-0.128***
Subprime	0.647	0.372	0.275***	1.109	0.754	0.355***	0.08***
Prime	5.603	2.968	2.634***	13.683	7.63	6.053***	3.419***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the mean loan amount (₹million) at the pin code-month level for Fintechs (Panel A) and Banks (Panel B). High and low exposure identify pincodes with above and below median UPI Exposure as calculated from (1). Data spans the period October 2015 - January 2019. Pre refers to the period before November 2016 and Post thereafter. Means for the pre- versus post and high versus low-exposure are as indicated. The difference between the post versus pre for low-exposure pincodes is shown in column 3. The difference between the post versus pre for high and low-exposure pincodes is shown in column 6. The difference-in-differences (column 6-column 3) is shown in column 7.

Table IA3
Impact on Credit: Economic Magnitudes

	All		Subprime		New-to-credit	
	Val.	Vol.	Val.	Vol	Val.	Vol
All Credit	0.56	0.67	0.46	0.55	0.13	0.28
FinTech Lenders	56.0	80.8	23	39.8	45	83.2
Banks	0.54	0.55	0.44	0.37	0.12	0.19

Notes: This table presents estimates of economic significance for regressions estimated in Equation 3. Each number refers to the coefficient scaled by the pre-period mean. Each row is a lender and each column shows the score band. The coefficients in the odd and even columns is for amount (₹million) and number of loans, respectively.

Table IA4
Robustness without Grid Fixed Effects: Impact on UPI

	(1)	(2)
Dependent variable	UPI value (₹Million)	UPI volume (in 1000s)
High UPI Exposure	4.514***	1.800***
	(0.290)	(0.119)
R^2	0.415	0.441
District-time FE	Y	Y
Dep. var mean	8.949	3.899
N	238350	238350

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the OLS estimates for the impact of exposure on UPI transactions. Observations are at the pincode level at monthly frequency for the period January 2017 to January 2019. The dependent variables in columns (1) and (2) are the value of all UPI transactions in ₹million and the number of UPI transactions in thousands, respectively. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA5
Robustness without Grid Fixed Effects: Impact on Credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score Band	All		Subprime		NTC		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High UPI Exposure × Post	3.016***	24.318***	0.127***	1.098***	-0.062***	1.595***	2.420***	16.966***
	(0.247)	(2.107)	(0.013)	(0.110)	(0.018)	(0.211)	(0.197)	(1.452)
R^2	0.936	0.902	0.830	0.784	0.903	0.930	0.911	0.892
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	9.746	61.896	0.564	3.702	2.507	19.660	5.304	30.062
Post-UPI Mean	15.544	108.603	0.892	6.333	2.503	23.863	9.740	61.097
Dep. var mean	13.659	93.423	0.785	5.478	2.504	22.497	8.298	51.011
N	508840	508840	508840	508840	508840	508840	508840	508840

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the impact of exposure on overall, subprime, New-to-credit and Prime credit. Observations are at the pincode level at monthly frequency for the period October 2015 to January 2019. The dependent variables in odd columns is the value of all loans in ₹million and the dependent variable in the even columns is the number of loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA6

Robustness without Grid Fixed Effects: Impact on Credit by Lender

	(1)	(2)	(3)	(4)
Lender	Fintechs		Banks	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act
	Panel A: Full sample			
High UPI Exposure × Post	0.105***	5.237***	2.911***	19.112***
	(0.011)	(0.484)	(0.237)	(1.692)
R^2	0.426	0.476	0.939	0.936
Pre-UPI Mean	0.002	0.070	9.743	61.827
Post-UPI Mean	0.190	9.622	15.356	99.066
Dep. var mean	0.129	6.518	13.532	86.964
	Panel B: Subprime sample			
High UPI Exposure × Post	0.008***	0.481***	0.119***	0.621***
	(0.001)	(0.048)	(0.012)	(0.069)
R^2	0.504	0.485	0.828	0.789
Pre-UPI Mean	0.000	0.013	0.563	3.689
Post-UPI Mean	0.015	0.928	0.877	5.414
Dep. var mean	0.010	0.630	0.775	4.853
	Panel C: New-to-credit sample			
High UPI Exposure × Post	0.017***	1.331***	-0.080***	0.269*
	(0.002)	(0.124)	(0.018)	(0.153)
R^2	0.544	0.512	0.901	0.945
Pre-UPI Mean	0.000	0.018	2.506	19.642
Post-UPI Mean	0.035	2.623	2.468	21.263
Dep. var mean	0.024	1.777	2.480	20.736
	Panel D: Prime sample			
High UPI Exposure × Post	0.054***	1.846***	2.366***	15.132***
	(0.006)	(0.172)	(0.192)	(1.301)
R^2	0.272	0.472	0.914	0.912
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.023	5.303	30.039
Post-UPI Mean	0.094	3.265	9.648	57.861
Dep. var mean	0.063	2.211	8.236	48.819
N	504280	504280	508840	508840

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the impact of exposure for Fintech and Banks on all credit (Panel A), subprime borrowers (Panel B), new-to-credit borrowers (Panel C), and prime borrowers (Panel D). Observations are at the pincode level at monthly frequency for the period October 2015 to January 2019. The dependent variable in odd columns is the value of all loans in ₹million. The dependent variable in even columns is the number of loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode clustered standard errors are shown in parantheses.

Table IA7
Robustness with Pincode Pairs: Impact on UPI

	(1)	(2)
Dependent variable	UPI value (Million INR)	UPI volume (in 1000s)
High UPI Exposure	5.636***	2.226***
	(0.528)	(0.205)
R^2	0.686	0.689
Neighbourhood-time FE	Y	Y
Dep. var mean	10.322	4.401
N	170100	170100

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the OLS estimates for the impact of exposure on UPI transactions. Remaining variable definitions and specifications are as in Table IA4. Fixed effects are included as indicated.

Table IA8
Robustness with Pincode Pairs: Impact on Credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score Band	All		Subprime		NTC		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High UPI Exposure × Post	4.132***	31.740***	0.190***	1.432***	-0.092***	2.116***	3.297***	22.282***
	(0.401)	(3.491)	(0.021)	(0.192)	(0.032)	(0.392)	(0.324)	(2.376)
R^2	0.972	0.956	0.935	0.929	0.976	0.972	0.961	0.949
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
Neighbourhood-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	12.480	81.173	0.685	4.782	3.155	25.737	6.897	39.586
Post-UPI Mean	19.880	142.324	1.051	7.865	3.140	31.210	12.631	80.720
Dep. var mean	17.475	122.450	0.932	6.863	3.145	29.431	10.768	67.352
N	428000	428000	428000	428000	428000	428000	428000	428000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the impact of exposure on overall, subprime, New-to-credit and Prime credit. Observations are at the pincode level at monthly frequency for the period October 2015 to January 2019. The dependent variables in odd columns is the value of all loans in ₹million and the dependent variable in the even columns is the number of loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA9

Robustness with Pincode Pairs: Impact on Credit by Lender

	(1)	(2)	(3)	(4)
Lender	Fintechs		Banks	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act
	Panel A: Full sample			
High UPI Exposure × Post	0.141***	6.199***	4.101***	26.721***
	(0.023)	(0.752)	(0.419)	(3.205)
R^2	0.662	0.748	0.974	0.971
Pre-UPI Mean	0.004	0.095	12.476	81.078
Post-UPI Mean	0.257	12.458	19.624	129.866
Dep. var mean	0.174	8.440	17.301	114.010
	Panel B: Subprime sample			
High UPI Exposure × Post	0.009***	0.585***	0.192***	0.879***
	(0.002)	(0.075)	(0.021)	(0.143)
R^2	0.756	0.750	0.935	0.947
Pre-UPI Mean	0.001	0.018	0.684	4.764
Post-UPI Mean	0.020	1.205	1.031	6.660
Dep. var mean	0.014	0.819	0.918	6.044
	Panel C: New-to-credit sample			
High UPI Exposure × Post	0.022***	1.567***	-0.138***	0.055
	(0.003)	(0.203)	(0.037)	(0.368)
R^2	0.772	0.762	0.975	0.980
Pre-UPI Mean	0.001	0.023	3.155	25.714
Post-UPI Mean	0.046	3.381	3.094	27.829
Dep. var mean	0.032	2.290	3.114	27.141
	Panel D: Prime sample			
High UPI Exposure × Post	0.078***	2.203***	3.327***	21.603***
	(0.015)	(0.261)	(0.345)	(2.443)
R^2	0.577	0.748	0.963	0.958
Pincode FE	Y	Y	Y	Y
Neighbourhood-time-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.032	6.896	39.554
Post-UPI Mean	0.128	4.230	12.503	76.490
Dep. var mean	0.087	2.866	10.680	64.486
N	428000	428000	428000	428000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the impact of exposure for Fintech lenders on all credit (Panel A), subprime borrowers (Panel B), new-to-credit borrowers (Panel C), and prime borrowers (Panel D).Observations are at the pincode level at monthly frequency for the period October 2015 to January 2019. The dependent variable in odd columns is the value of all loans in ₹million. The dependent variable in even columns is the number of loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). Post is a dummy, which takes value 1 from November 2016 onwards. Fixed effects are included as indicated. Pincode clustered standard errors are reported in parantheses.

Table IA10
Open API: Impact on Credit by Lender

	(1)	(2)	(3)	(4)
Lender	Fintechs		Banks	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act
	Panel A: Full sample			
API Exposure × High UPI Exposure	0.231***	12.686***	3.454***	26.276***
	(0.036)	(1.965)	(0.409)	(2.971)
High UPI Exposure	0.049***	2.123***	1.918***	11.609***
	(0.012)	(0.530)	(0.243)	(1.719)
API Exposure	-0.017	-0.703	-0.059	-3.633
	(0.021)	(1.032)	(0.291)	(2.233)
R^2	0.467	0.538	0.947	0.946
Pre-UPI Mean	0.002	0.069	9.744	61.747
Post-UPI Mean	0.192	9.726	15.424	99.936
Dep. var mean	0.127	6.444	13.533	86.851
	Panel B: Subprime sample			
API Exposure × High UPI Exposure	0.015***	1.169***	0.110***	0.809***
	(0.002)	(0.196)	(0.022)	(0.113)
High UPI Exposure	0.004***	0.198***	0.090***	0.398***
	(0.001)	(0.054)	(0.013)	(0.088)
API Exposure	0.000	-0.021	0.026	-0.054
	(0.002)	(0.103)	(0.022)	(0.092)
R^2	0.548	0.541	0.847	0.846
Pre-UPI Mean	0.000	0.013	0.563	3.684
Post-UPI Mean	0.015	0.939	0.874	5.440
Dep. var mean	0.010	0.623	0.776	4.854
	Panel C: New-to-credit sample			
API Exposure × High UPI Exposure	0.040***	2.705***	0.046	1.236***
	(0.006)	(0.411)	(0.030)	(0.269)
High UPI Exposure	0.008***	0.679***	-0.071***	0.120
	(0.002)	(0.149)	(0.020)	(0.179)
API Exposure	-0.001	-0.194	-0.010	-0.075
	(0.003)	(0.237)	(0.023)	(0.213)
R^2	0.595	0.570	0.903	0.948
Pre-UPI Mean	0.000	0.017	2.511	19.629
Post-UPI Mean	0.036	2.647	2.464	21.395
Dep. var mean	0.024	1.757	2.486	20.723
	Panel D: Prime sample			
API Exposure × High UPI Exposure	0.117***	4.763***	2.777***	20.234***
	(0.021)	(0.712)	(0.339)	(2.305)
High UPI Exposure	0.025***	0.650***	1.539***	9.120***
	(0.007)	(0.172)	(0.192)	(1.244)
API Exposure	-0.015	-0.304	-0.099	-3.029*
	(0.012)	(0.376)	(0.237)	(1.734)
R^2	0.306	0.533	0.926	0.928
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.023	5.299	29.992
Post-UPI Mean	0.095	3.304	9.712	58.443
Dep. var mean	0.063	2.186	8.231	48.738
N	459392	459392	463462	463462

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the triple difference estimates for the interacted effect of UPI exposure and API Exposure on overall (Panel A), subprime (Panel B), new-to-credit (Panel C), and prime credit (Panel D), by Fintechs and banks. Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. The dependent variable in columns 1 and 3 is the value of all loans in ₹million, and the dependent variable in columns 2 and 4 is the number of unique loans. High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). API Exposure is a continuous variable, varying at the pincode-month level, as defined in Equation (5). Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA11
Robustness for Financial Formalization: Impact on Credit by JDY subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
Lender	All		Fintech		New-to-credit+Fintech	
Dependent var.	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act Act
	Panel A: High JDY					
High UPI Exposure × Post	3.885***	31.411***	-0.022	2.399***	0.022***	1.662***
	(0.504)	(4.594)	(0.037)	(0.518)	(0.004)	(0.314)
R^2	0.947	0.923	0.916	0.947	0.630	0.622
Pre-UPI Mean	14.069	90.476	3.517	28.337	0.001	0.027
Post-UPI Mean	22.426	158.634	3.496	34.163	0.051	3.731
Dep. var mean	19.710	136.483	3.503	32.269	0.035	2.527
N	290400	290400	290400	290400	288640	288640
	Panel B: Low JDY					
High UPI Exposure × Post	0.402**	2.365	-0.038***	-0.049	0.003	0.209*
	(0.162)	(1.601)	(0.014)	(0.231)	(0.002)	(0.121)
R^2	0.894	0.906	0.884	0.894	0.558	0.656
Pincode FE	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	3.745	23.446	1.029	7.758	0.000	0.006
Post-UPI Mean	6.029	42.054	1.044	9.856	0.014	1.126
Dep. var mean	5.287	36.006	1.039	9.174	0.010	0.762
N	187160	187160	187160	187160	184760	184760

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the differential impact of UPI exposure on Fintech credit in pincodes with high JDY bank accounts (Panel A) and low JDY bank accounts (Panel B). Columns 1-2 include all loans, while columns 3-4 is the subsample of New-to-credit loans. Observations are at the pincode level at monthly frequency for the period October 2015 to January 2019. The dependent variable in odd columns is the value of all loans in ₹million. The dependent variable in even columns is the number of loans. High exposure is 1 for above-median exposure, defined as in Equation (1). High JDY and low JDY refer to subsamples when a pincode's cumulative number of JDY bank accounts is above or below the first tercile, as of November 2016 . Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA12
Impact on UPI by Connectivity with Jio

	(1)	(2)
Dependent variable	UPI value (Million INR)	UPI volume (in 1000s)
$\text{Early}_{\text{Jio}}$	3.966***	1.597***
	(0.305)	(0.128)
R^2	0.487	0.513
Grid-time FE	Y	Y
District-time FE	Y	Y
Dep. var mean	8.967	3.906
N	231975	231975

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the OLS estimates for the impact of early exposure to Jio towers on UPI transactions. Observations are at the pincode level at monthly frequency from January 2017 to January 2019. The dependent variables in columns (1) and (2) are the value of all UPI transactions in ₹million and the number of UPI transactions in thousands respectively. $\text{Early}_{\text{Jio}}$ is 1 for pincodes with distance to a Jio tower less than 6 km, as of 2017 Q1. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA13
Robustness for Connectivity to Jio: Impact on Credit by Jio Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lender	Fintech				Banks			
Sample	All		New-to-credit		All		New-to-credit	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
	Panel A: Early Jio							
High Exposure × Post	0.337***	13.546***	0.046***	3.087***	6.404***	46.072***	-0.089	1.859***
	(0.064)	(2.984)	(0.010)	(0.732)	(1.059)	(8.016)	(0.069)	(0.687)
R^2	0.501	0.584	0.645	0.622	0.959	0.959	0.893	0.949
Pre-UPI Mean	0.002	0.069	0.000	0.017	9.744	61.747	2.511	19.629
Post-UPI Mean	0.384	18.353	0.068	4.738	26.826	182.273	3.773	36.625
Dep. var mean	0.127	6.444	0.024	1.757	13.533	86.851	2.486	20.723
N	163100	163100	163100	164173	164173	164173	164173	
	Panel B: Late Jio							
High Exposure × Post	0.048*	5.438**	0.015**	2.206**	2.079**	12.453**	0.273*	1.142
	(0.026)	(2.488)	(0.007)	(0.880)	(1.000)	(6.085)	(0.154)	(1.255)
R^2	0.724	0.759	0.636	0.754	0.945	0.957	0.893	0.921
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.069	0.000	0.017	9.744	61.747	2.511	19.629
Post-UPI Mean	0.057	4.544	0.016	1.575	6.268	34.409	1.333	8.906
Dep. var mean	0.127	6.444	0.024	1.757	13.533	86.851	2.486	20.723
N	61463	61463	61463	61463	61830	61830	61830	61830

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the difference-in-difference estimates for the differential impact of UPI exposure on Fintech and credit in pincodes with early (Panel A) and late access (Panel B) to a Reliance Jio tower. Columns 1-2, and 5-6 include all loans, while columns 3-4 and 7-8 is the subsample of new-to-credit loans. Observations are at the pincode level at monthly frequency for the period October 2015 to January 2019. The dependent variable in odd columns is the value of all loans in ₹million. The dependent variable in even columns is the number of loans. High exposure is 1 for above-median exposure, defined as in Equation (1). Early Jio and Late Jio refer to subsamples when a pincode's distance to an active 4G Jio tower is less than/more than 6 km, as of 2017 Q1 . Fixed effects are included as indicated. Pincode clustered standard errors are shown in parantheses.

Table IA14
Connectivity With Jio: Non-Jio Subsample

	(1)	(2)	(3)	(4)
Sample	All		New-to-credit	
Dependent var.	Amt (₹million)	Act	Amt (₹million)	Act
	Panel A: Fintechs			
$\text{Early}_{\text{Jio}}$ × High UPI Exposure × Post	0.185***	6.082**	0.025***	1.152*
	(0.056)	(2.631)	(0.009)	(0.674)
High Exposure × Post	0.076*	5.339***	0.014**	1.575***
	(0.040)	(1.997)	(0.007)	(0.524)
$\text{Early}_{\text{Jio}}$ × Post	0.042	4.235**	0.013**	1.323**
	(0.041)	(2.145)	(0.006)	(0.536)
R^2	0.459	0.541	0.595	0.572
Pre-UPI Mean	0.002	0.069	0.000	0.017
Post-UPI Mean	0.452	21.059	0.078	5.329
Dep. var mean	0.127	6.444	0.024	1.757
	Panel B: Banks			
$\text{Early}_{\text{Jio}}$ × High UPI Exposure × Post	4.288***	33.928***	-0.108	1.866**
	(1.100)	(8.344)	(0.087)	(0.810)
High Exposure × Post	1.795**	8.229	-0.042	-0.843
	(0.802)	(6.155)	(0.081)	(0.640)
$\text{Early}_{\text{Jio}}$ × Post	1.443*	10.993*	-0.034	0.107
	(0.793)	(5.981)	(0.080)	(0.585)
R^2	0.944	0.944	0.907	0.953
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	9.744	61.747	2.511	19.629
Post-UPI Mean	30.926	213.721	4.255	42.568
Dep. var mean	13.533	86.851	2.486	20.723
N	187680	187680	187680	187680

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the triple difference estimates for the impact of UPI exposure on credit in pincodes with early access to a Jio tower, relative to late access in the post period, for a sample of Fintech loans (Panel A) and Banks (Panel B). Columns 1–2 include all loans, while columns 3–4 is the subsample of new-to-credit loans.Underlying observations are at the pincode level at the monthly frequency for the period October 2015 to January 2019. The dependent variables are value loans in ₹million (columns 1, 3, 6) and the number of loans (columns 2, 4, 6). High exposure is a dummy variable that identifies pincodes with above-median exposure, defined as in Equation (1). $\text{Early}_{\text{Jio}}$ takes a value 1 when a pincode's distance to an active 4G Jio tower is less than 6 km, as of Q1 2017. The estimates are for a subsample of pincodes which have an active non-Jio 4G tower, as of 2017 Q1. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA15

Robustness for Digital Verifiability of Revenues: Evidence from a Large Fintech Lender for the Sub-sample with Internal Credit Scores

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Loan Size (in 000's)		Interest Rate (in %)		Internal Credit Score	
Log(QR T.Value)	39.731***		-0.030***		1.533***	
	(1.226)		(0.002)		(0.033)	
Log(QR T.Count)		33.430***		-0.028***		1.314***
		(0.945)		(0.001)		(0.031)
R^2	0.173	0.155	0.080	0.081	0.239	0.224
State Time FE	Y	Y	Y	Y	Y	Y
Dep Var Mean	106.355	106.355	1.892	1.892	15.055	15.055
N	18973	18973	18973	18973	18973	18973

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents evidence regarding the digital verifiability of revenue through QR-based UPI transactions and credit outcomes using data from a large Fintech lender. Observations are at the loan level. Data is for 2020-2023. The dependent variable in columns 1–2 is the lender's loan size in thousands. The dependent variable in columns 3–4 is the interest rate in (%). The dependent variable in columns 5–6 is the internal credit score dummy that identifies customers who have been assigned an internal credit rating by the fintech lender. The dependent variable in columns 5–6 is the internal credit score. QR-UPI T.Value and QR-UPI T.Count are monthly QR-code-based UPI transaction values, and transaction frequency is at the loan-borrower-month level. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.