Open Banking and Digital Payments: Implications for Credit Access

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Abstract

Does the ability to generate verifiable digital financial histories, with customers having data-sharing rights, improve credit access? We answer this using India's launch of an Open-Banking based public 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, including increased credit to subprime and new-to-credit customers. We show several mechanisms at play: low-cost internet improves credit access, lenders weigh in digital histories, and digital payments with Open Banking effectively complement first-time bank accounts enabling access to formal credit.

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1 Introduction

Financial inclusion is a key reform agenda for policymakers across the world. Though household access to savings accounts has improved over the past decade, access to credit remains elusive for the newly banked population, primarily due to a lack of sufficient credit history.[1] Open Banking provides a possible solution. By moving data ownership from the financial intermediary to consumers, Open Banking allows customers to share verifiable records of their financial transactions across financial intermediaries with borrower consent overcoming traditional information asymmetries (Parlour et al., 2022; Babina et al., 2024). Key here is the ability to share verifiable financial histories expediently with low transaction costs. Such alternate data can be used to assess creditworthiness of borrowers with thin or no credit histories (Berg et al., 2020; Chioda et al., 2024). The public provision of zero-cost payment systems through Digital Public Infrastructure allows such effective sharing of information since customers can generate a costless, digitally verifiable financial history.

Using India's 2016 launch of the Unified Payments Interface (UPI) as a natural experiment, we analyze whether the public provision of digital payment infrastructure combined with Open Banking enhances access to credit. UPI is the earliest implementation of an open-banking based payment infrastructure that is free for customers and enables them to create verifiable digital financial footprints in real time. Importantly, customers own their data and can share their UPI transaction history across financial intermediaries.

Two features make India an ideal setting to answer this question. First, India has a large, financially underserved population. Second, India was an early mover in building scalable Digital Public Infrastructure to foster competition and improve financial inclusion. The costs of building and operating UPI were borne by the National Payments Corporation of India (NPCI), a quasi-government entity. Importantly, by virtue of its zero interchange fees, UPI enabled a customer consent-driven real-time, zero-cost (to customer: retail & merchant) creation of a verifiable digital financial history shareable across intermediaries. Within a short time span, UPI led to exponential penetration of digital payments across India and is used at all levels from street vendors to large shopping malls. As of October 2023, UPI accounts for 75% of all retail digital payment transactions in India, with over 300 million individuals and 50 million merchants.[2]

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

[2]See https://pib.gov.in/Pressreleaseshare.aspx?PRID=1973082 and https://indbiz

This paper establishes five main findings. First, UPI significantly expanded consumer credit access both on the intensive (included borrowers) and extensive (excluded borrowers) margins, particularly for traditionally underserved borrowers. Importantly, credit increases for both the incumbent banks and the new entrants (fintechs). Financial inclusion improves, particularly benefiting marginal borrowers such as subprime and new-to-credit borrowers (i.e., borrowers who did not have access to formal credit markets earlier). Second, Fintech lenders led the credit increase to new-to-credit borrowers, especially in ex-ante financially excluded regions. Third, an alternative empirical design using the 4G launch of a major mobile phone operator that significantly reduced internet data costs corroborates these findings and underscores the importance of digital inclusion in expanding financial access. Fourth, using detailed loan-level data from one of the largest fintech lenders, we pin down an important mechanism: lenders use UPI transactions in their credit assessment and approval decisions. Finally, we find the credit increase is not accompanied by any discernible increase in default rates. Overall, our study highlights how Open Banking combined with the public digital payments infrastructure can expand credit access. Ours is the first large sample study examining the impact of Open Banking in the form of open publicly funded digital payment infrastructure on credit markets.

We are able to access and combine several unique and proprietary datasets that allow us to comprehensively examine the impact of Open Banking on credit markets in India. Our primary dataset is a comprehensive, proprietary, credit registry data on the *universe of consumer loans* from Transunion CIBIL, rarely made available to researchers. This data is at the pincode-quarter level from the first quarter of 2015 to the first quarter of 2019. 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 Open Banking affects banks relative to fintechs, and how it affects financial inclusion. We use novel regulatory data on deposits from the Reserve Bank of India (RBI) to construct our pincode-level UPI exposure measure. We are also able to obtain proprietary data on the main explanatory variable, UPI transaction volume and rupee value, at the pincode-quarter level from the State Bank of India (SBI), which is one of the top five payment service providers. Three additional datasets help us pin down the mechanisms: (i) regulatory data on Jan Dhan Yojana (JDY) accounts from the Department of Financial Services (Government of India), (ii) 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 (iii) loan-level data from one of the largest fintech lenders in India, that lends to roadside kiosks which has detailed borrower

.gov.in/upi-transactions-to-reach-1-bn-daily-by-fy27-report/

and loan characteristics, as well as the lender's internal credit score and the borrower's monthly UPI transactions.

We find that credit increased rapidly in 2015-2019, with fintech credit volumes growing nearly 10x in the subprime and new-to-credit segment. Despite minimal presence in 2015, the number of subprime and new-to-credit loans by fintechs nearly equaled that of the banks by 2019. Further, the headline aggregate correlation between the UPI transaction volume and credit shows a striking 7% increase in credit for a 10% increase in UPI payments. Of course, this relationship may not be causal if common factors drive UPI usage and credit. Our main empirical strategy relies on the staggered adoption of UPI by banks (Dubey and Purnanandam, 2024). We rely on two key insights to generate exogenous pincode-level variation. 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, network externalities in the adoption of digital payments (Crouzet et al., 2023; Higgins, 2024) imply that regions served by early adopter banks were catalyzed into further UPI uptake. We construct the ex-ante fraction of deposits (as of March 2016) of early adopter banks in each pincode[3]. Pincodes with above median values are defined as high-exposure and low-exposure otherwise. We show that high-exposure pincodes exhibit higher UPI usage, validating our exposure measure. Univariate balance tests show no statistically significant differences in either levels or growth in economic activity or credit across high- and low-exposure pincodes prior to the launch of UPI.

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; our granular pincode-level UPI measure allows us to control for district-by-time (usually the unit at which national policies operate) and pincode fixed effects which absorbs time-invariant differences between treatment and control groups. The canonical identifying assumption in our difference-in-differences setup requires that treated and control pincodes exhibit similar patterns in the counterfactual absent treatment, conditional on district-by-quarter fixed effects. We find no statistically significant trend difference in credit between the two groups in the pre-treatment period.

What is the effect on access to credit? Credit in high-exposure pincodes increases by

[3]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.

nearly 15% relative to the pre-treatment mean. Potentially, the positive effect of open digital payment services on credit outweighs the negative effect due to banks' weakened incentives to produce "soft information." Weakened bank incentives hurt credit supply only if fintech entry and the open digital payment infrastructure cannot substitute for the information production expertise of banks. In fact, credit increases across borrower risk profiles — subprime, new-to-credit, and prime.

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 Banking 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). Open Banking through Digital Public Infrastructure addresses incumbents such as banks' disincentives in generating digital data.

Insofar as open digital payments lower the cost of evaluating borrower's credit risk, in principle, both traditional intermediaries and fintech can leverage individual-level payment data to lend to underserved households. However, fintech lenders face lower regulatory restrictions, are quicker to adopt technological innovations, are faster at processing loans, and have lower operating costs due to automated online underwriting (Buchak et al., 2018; 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). The opportunity cost of catering to the underserved markets may also be higher for traditional banks, who specialize in bigger ticket loans to the prime segments. Indeed, by revealed preference, banks did not serve such consumers pre-UPI. Hence, it is important to examine the heterogeneity between fintechs and banks. Fintechs in high UPI exposure pincodes had 40.5x (77x) larger loan value (volume) than pre-period, partly attributable to the low base pre-UPI. In comparison, bank lending increases by a relatively modest 14% in value and 13% in the number of loans in high exposure pincodes. Fintech credit to subprime and new-to-credit borrowers increases by 40x and 102x in terms of the number of unique loans. For banks, credit is highest for prime borrowers, with only a muted increase for subprime and new-to-credit borrowers. Overall, Open Banking promotes market segmentation, with new fintech entrants targeting new marginal borrowers rather than competing with banks for the already included borrowers (Boot and Thakor, 2024).

For additional robustness, we modify our empirical design to control for time-varying factors within narrow geographies within districts. To capture more granular geographical effects, we construct grids (similar to Moscona et al. (2020)) by dividing the Indian map into rectangular units of size 0.4×0.4 degrees. Our estimates are identified through within-grid variation in UPI exposure across pincodes. In an alternate test, we examine neighboring pincodes (similar to Beerli et al. (2021)) and include only those low-exposure pincodes in the control group that share a boundary with a high-exposure pincode. We assign a pair id and compare within pincode pairs. In both sets of tests, our results remain qualitatively the same.

To nail down that Open Banking payments infrastructure enabled underserved borrowers to access the credit markets, we examine heterogeneity across regions with a high and low take-up in "Jan Dhan Yojana" (JDY) accounts. The JDY scheme was introduced in 2014 as part of India's national financial inclusion mission to facilitate basic savings accounts for the unbanked, and significantly boosted bank account access (Agarwal et al., 2017). Since UPI requires a bank account to operate, JDY ensured that the environment was primed for UPI take-off. We hypothesize that the effect on new-to-credit loans should be greater in regions with more new-to-banking customers with no/thin credit history (induced by the JDY scheme). Indeed, we find that fintech loans to new-to-credit borrowers are higher in regions with more JDY account holders. Our results suggest open digital payments complement savings bank account-oriented financial inclusion programs in expanding credit access.

To further strengthen the causal interpretation of our findings and nail the mechanism, we exploit the fact that UPI usage requires access to fast, reliable, and low-cost internet. In 2016, Reliance Jio launched 4G services, improving network coverage and lowering internet access costs, bridging the digital inclusion gap. Prices for 1 GB of data dropped from ₹228 in 2015 to ₹9 in 2020. The average distance of the centroid of a pincode 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 based on the entry of non-Jio towers and find only muted effects, underscoring the complementarity between digital inclusion due to low-cost internet access and Open Banking-based payment technology in expanding credit access to marginal borrowers.

Finally, we use loan-level data from a large fintech lender to assess how it incorporates UPI transaction information in its lending decisions. Our data includes all loans to roadside kiosk owners for 2020-2023 and has information on the loan size, interest rate, and, importantly, for our analysis, the kiosks' monthly UPI transactions and the lender's internal credit score. Consistent with the baseline, UPI transactions positively correlate with the loan amount and negatively correlate with interest rates. UPI transactions are positively correlated with the lender's internal credit score, showing the direct link between the lender's credit assessment decisions and UPI transaction data.

In additional tests, we show that the credit increases do not translate to higher default rates. Alternate UPI-based information enabled lenders to expand credit to underserved, creditworthy borrowers without taking on additional default risk.

Related literature We contribute to several strands of the literature. First, we expand recent work on the welfare implications of Open Banking for consumers (Parlour et al., 2022; Goldstein et al., 2023; He et al., 2023; Babina et al., 2024). Ours is the first large sample study to examine the impact of Open Banking in the form of publicly funded digital payment infrastructure on credit markets. Despite the potential for conflicts between incumbents (banks) and entrants (fintechs), overall, we find increased credit access across lenders and across borrower groups.

Second, our paper speaks to the literature on financial inclusion via access to savings bank accounts (Agarwal et al., 2017; Dupas et al., 2018; Bachas et al., 2021; Breza et al., 2024). The bigger challenge for financial inclusion is enabling access to formal credit markets. Here, bank accounts alone are often not sufficient. Our study emphasizes that digital payments and Open Banking are very effective in complementing bank accounts to enable actual access to formal credit, even for those who were previously excluded from these markets.

Third, our study also complements the large and growing literature on the determinants and effects of fintech credit growth. Berg et al. (2022) provides a survey of this literature. While the extant literature highlights the potential for technology-driven cost savings in expanding access to finance, direct empirical evidence of an increase in financial access remains scarce (e.g., Buchak et al. (2018); Fuster et al. (2019); Bartlett et al. (2022); Balyuk et al. (2022); Gopal and Schnabl (2022); Babina et al. (2024)). In our setting, credit increases to traditionally excluded borrowers, i.e., new-to-credit and subprime borrowers. While the fintechs in previous studies had to privately invest in technology or partnerships to create alternate data sources to assess customers' credit risk, the cost of payment infrastructure in India was borne by NPCI, a quasi-government entity. The free digital payment infrastructure allowed lenders to establish a digital trail of financial transactions for each user, making it easier to assess income, consumption, and credit risk, explaining their willingness to lend to marginal borrowers.

Finally, our paper complements the recent literature on cashless payments (Ouyang, 2022; Sarkisyan, 2023; Dubey and Purnanandam, 2024; Ghosh et al., 2024). Focusing on data from a single fintech entity, Ouyang (2022), Ghosh et al. (2024), and Agarwal et al. (2024) document that cashless transactions enable access to credit. Using the launch of UPI as a natural experiment Dubey and Purnanandam (2024) provides evidence of the 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 in a variety of ways. First, we examine the impact of Open Banking where the customer decides on whether and to whom to share data and can apply simultaneously to multiple banks or fintechs for credit at the push of a button to share a verifiable digital payment history at zero cost. Absent Open Banking, the fintech or the website exercises its discretion or monopoly power in making credit decisions hence the aggregate effects can be very different from an economy where the customer owns the data. Second, unlike most papers that obtain data from a single fintech, we have data from the credit bureau on the universe of consumers allowing us to examine effects on credit across different kinds of customers (prime, sub-prime, new to credit) by different kinds of intermediaries (banks and fintechs). This is important in assessing the overall impact on credit markets.

This study contributes not just to the academic literature but also helps inform policymakers. India's experiment with open banking and public investment in digital infrastructure (UPI) 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-Banking based Digital Public Infrastructure — affects access to credit, and in particular financial inclusion through first-time access to formal credit markets.

2 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 interoperably. 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 the 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 integrate onto the UPI network via APIs. UPI has also bridged the gap between traditional banking and technology, enabling financial access. 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 1% increase in UPI is associated with a 0.7% increase in credit (Figure 1). The rise in UPI allowed lenders, primarily the fintech lenders that operate within the digital realm, to access alternate 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[4]. 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

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

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.

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 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.

3 Data and Empirical Strategy

3.1 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.[5] 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[6] at the quarterly frequency for the period Q1 2015–Q4 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.

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

[6] 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 a formal credit history that would return a score, and hence this category has the highest information asymmetry between lender and borrower. Importantly, for our purposes, the various credit score categories allow us to study how Open Banking 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 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, 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.[7]

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 3.2 and describe the details of the underlying data here. Information on bank-wise UPI adoption is publicly available.[8] 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,

[7]Internet Appendix Table IA1 reports these correlations.

[8]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 neighbourhoods 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 banks (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-quarter level for our analysis for the period Q1-2017 to Q1-2019. 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.

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-quarter level from the Department of Financial Services, Government of India. This data covers the period Q3 2014-Q3 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, 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 Q3 2016–Q1 2019.

Micro data from the largest fintech firm Finally, we supplement our 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, 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.

3.2 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 November 2016.[9] 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 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 predict UPI usage. To construct the exposure measure, we use the data on bank-wise deposits at the pincode-bank level. We take 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 November 2016 as 'early' adopter banks, since

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

the GoI makes this data publicly available. [10]

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

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

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, we focus on very narrow neighborhoods, namely, pincodes. A higher level of aggregation, such as at the district level, may 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×time fixed effects that control for time-varying factors at the district level in a non-parametric way. Nonetheless, other time-varying changes (contemporaneous to the UPI launch) at the pincode level could still correlate with the UPI exposure measure. Appendix Table A2, 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

[10] 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.

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:

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

for pincode p in district $d(p)$ in quarter-year t. Observations are at the pincode-quarter level for Q3-2016 to Q4-2019. $Y_{pd(p)t}$ 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 (2). 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 quarterly UPI transaction value of ₹4 million higher than low-exposure pincodes. Relative to the mean of ₹32.218 million, this corresponds to a 12.4% 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 million or by 12% 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.

3.3 Descriptive statistics

Table 1 presents the summary statistics for key variables. Early adopter banks have a median (mean) deposit market share of 69% (60%) 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 12,493 pincodes in our sample, 1,799 pincodes have zero exposure and 111 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-quarter level, the mean (median) number of UPI transactions stood at 14 (4) thousand, while the mean (median) value of transactions was ₹32 (₹8) million. Along the credit dimension, the mean (median) number of new loans sanctioned was 290 (64), totalling ₹42 (₹11) million in value. The amount of loans granted to new-to-credit borrowers was nearly ₹8 million on average, almost four times that of subprime borrowers (₹2.4 million). On the extensive margin, the mean number of loans to new-to-credit borrowers (70) is almost four times that of subprime loans (4) loans. There is heterogeneity across lenders. Fintechs are smaller players in the market with an average of ₹0.44 million loans compared to banks with an average of ₹41 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-Q3 2016.[11] 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.

3.4 Main empirical strategy

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

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

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

for pincode p belonging to district $d(p)$ in quarter-year t. Observations are at the pincode-quarter-year level from Q1 2015 to Q4 2019. Post_t takes a value of 1 from Q3 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, and $\alpha_{d(p)t}$ refers to the district×quarter 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×quarter fixed effect allows us to control for time-invariant and time-varying factors at the district-quarter level. Importantly, the treatment effects are identified within district×quarter 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×quarter 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.

Our key identification assumption follows the canonical difference-in-differences specification that requires that conditional on district-quarter 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 quarters in relative event-time interacted with High Exposure_p dummy analogous to the specification in Equation (3):

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

for pincode p belonging to district $d(p)$ in quarter t. Observations are also at the pincode-quarter-year level, and τ is an indicator for each quarter between Q1 2015 and Q4 2019. $Y_{pd(p)t}$ is the sanctioned amount (in ₹million) and accounts. High Exposure_p, $\alpha_{d(p)t}$, and θ_p are district×quarter 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 the quarter Q2 of 2016.

4 The effect of Open Banking on credit

Open Banking lets users 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 Banking 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 open banking 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 show a considerable uptick in these underserved segments. Starting from a very low base in 2015, the number of subprime and new-to-credit loans by fintechs nearly equaled that of the banks by the end of 2019. 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-difference setup requires that conditional on district-quarter 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 quarter in Q3 2015–Q4 2019 relative to the baseline Q2 2016 (denoted by the vertical dashed line). 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.

In 2017, RBI issued a circular that strengthened Open Banking through a multi-bank Payment-Service-Provider (PSP) model, in which a large merchant/tech player (referred to as a "third party app provider", for example, Gpay, Paytm, etc.) with access to large customer bases could connect to the UPI system through multiple PSP banks as opposed to the previous limit of only one bank.[12] A primary mechanism through which UPI increases credit availability is by creating a digital stream of alternative data that financial intermediaries can use to screen and acquire borrowers. The September 2017 circular essentially increased the amount of UPI transaction history available to lenders by allowing these merchants and tech players to access more granular data across banks. Moreover, the various banks could now access a much larger set of potential borrowers through the payment app. Consistent with this thesis, we find a sharper jump in credit in treated pincodes post-September 2017 (represented by the solid vertical line in Figure 5).

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$\times$Post, in column 1 shows a ₹4 million differential increase in loan value in high-exposure pincodes, representing a 15% increase relative to the pre-treatment mean. Column 2 shows a 16% 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 8% in rupee value terms and by 11% in the number of loans (columns 3–4). The number

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

of loans to new-to-credit borrowers increased by 4%, though it is muted in value terms (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 22% in value terms and by 24% 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.[13] 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

[13] 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)

pre-treatment period in either credit amount or number of loans.

Table 4 reports the average treatment effect estimates using Equation 3. Fintechs' loan amount increases on average by 0.16 million monthly, corresponding to a 40x increase in high-exposure pincodes relative to the pre-period mean (column 1, Panel A). Correspondingly, the number of loans increases by 5.8 (77x). In contrast, bank credit increases by 14% in value terms and 13% 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 ₹0.012 million, corresponding to a 120x increase (column 1, Panel B). The number of loans increases by 0.55 or 39x (column 2, Panel B). In contrast, bank lending to subprime borrowers increases by a relatively more modest 8% (=0.124/1.652) and 6% (=0.614/10.957), in value and quantity, respectively (columns 3 and 4, Panel B). Effects are similar for new-to-credit borrowers, with an increase of ₹0.028 million (28x) in loan value and 1.6 (102x) new loans for Fintechs (Panel C, columns 1 and 2) but displays muted 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.[14] 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

[14]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.

calculate the annualized growth in net credit flow (new consumer loans granted minus consumer loans repaid).[15] 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 capital expenditure (MPCE)[16]. Overall, the average size of the fintech loan is ₹27,778 (=₹0.162 million/5.832), representing nearly 4.30x (=₹27,778/₹6,459) of urban MPCE and 7.36x (=₹27,778/₹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 8.59x of urban MPCE and 12.52x of rural MPCE . Similarly, for subprime credit, this translates to nearly 21.99x and 32.05x 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), overall fintech credit translates to 12% of average annual income and 39% of the bottom 50$^{\text{th}}$ annual income percentile. Using the average monthly savings of ₹15,625 [17] as a benchmark, these estimates (1.78x) are meaningful and important.

Controlling for granular local economic factors One could argue that unobservable time-varying attributes or policy changes at the pincode level correlated with the launch of UPI could be driving credit increases. Government policies are usually targeted at the district level or other administrative unit levels and not the pincode level, ensuring that district-time fixed effects account for any variation arising from these policies. In addition, UPI exposure is uncorrelated ex-ante with either levels or growth in credit or economic activity (Section 3.2). We also see no clear pre-treatment differential trends in the outcome variables. Nonetheless, for additional robustness, we modify our empirical design to control for time-varying factors within narrow geographies within districts based on a

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

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

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

similar strategy in Moscona et al. (2020). To capture more granular geographical effects, 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. 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. We use the baseline specifications, Equation 4 and 3 and control for local time-varying economic factors in a non-parametric manner using (Grid $\times$ Time) fixed effects. Consistent with our baseline (Figure 5), the temporal dynamics do not display any discernible pre-trends (Internet Appendix Figure IA6). Other results remain robust (Internet Appendix Tables IA4–IA6).

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 $\times$ quarter fixed effects and show results remain robust (Internet Appendix Tables IA7–IA9).

5 Mechanisms

We examine two mechanisms enabling credit access: (i) the preceding rise in bank account holdings of (previously) financially excluded households and (ii) 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.

5.1 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:

$$\begin{aligned} Y_{pd(p)t} = & \alpha_{d(p)t} + \theta_p + \beta \times \text{Post}_t \times \text{High Exposure}_p + \gamma \times \text{HighJDY}_p \times \text{High Exposure}_p \\ & + \eta \times \text{Post}_t \times \text{High Exposure}_p \times \text{High JDY}_p + \epsilon_{pd(p)t} \end{aligned} \quad (5)$$

for pincode p belonging to district $d(p)$ in quarter-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 5 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.[18]

These tests further strengthen the thesis that the Open Banking 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.

5.2 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

[18] 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 5 and Internet Appendix Table IA10.

the specification:

$$Y_{pd(p)t} = \alpha_{d(p)t} + \theta_p + \gamma \times \text{Early}_{\text{Jio}} + \eta \times \text{High Exposure}_p \times \text{Early}_{\text{Jio}} + \epsilon_{pd(p)t} \tag{6}$$

for pincode p belonging to district $d(p)$ in quarter-year t. Observations are at the pincode-quarter level and span Q1 2015 to Q4 2019. $\text{Early}_{\text{Jio}}$ identifies pincodes that received a Jio tower within 6 km by 2017 Q1.[19] 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.[20]

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 IA11 confirms that early Jio pincodes indeed have higher UPI transactions. Table 6 reports the results for the impact on credit. Fintech lending increases in credit in high exposure pincode are driven

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

[20] See (Acemoglu et al., 2004; 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.

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 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.[21]

To further address the concern that high-exposure regions closer to mobile towers may be experiencing faster economic growth, we also obtain data on the location of non-Jio mobile towers. Since non-Jio operators did not similarly lower costs or increase speed, we exploit distance to non-Jio towers in placebo tests. We modify equation 6 and introduce an indicator that takes the value one for pincodes that were within 6 km of a non-Jio tower as of 2017 Q2. Similar to our Jio analysis, we then include a triple difference interaction (Non-Jio X High-Exposure X Post) that captures the differential effect of UPI exposure on credit in areas ex-ante covered by non-Jio towers relative to other areas. Results are shown in columns 5–6. Reassuringly, the coefficient estimate on this triple interaction is muted. The differential effect of Jio is 5 times that of non-Jio coverage. Effects are similar in Panel B when we examine bank lending. The triple interaction coefficient indicates a 5% increase in value and volume. New-to-credit bank lending is muted in terms of value and only 1% in terms of volume.

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 entirely driven by the early adopter pincodes (Internet Appendix Table IA12). 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. Second, the results on the horse race with non-Jio pincodes further emphasize that it is not just internet access that mattered for UPI adoption and the subsequent credit uptake. Our analyses highlight the complementarity between payment technology and low-cost and reliable internet access in expanding credit

[21]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 IA11 and reported in Table IA12 in the appendix.

access by allowing marginal borrowers to create a digitally verifiable trail of income.

5.3 Digital verifiability of revenues

Finally, we establish the direct link between UPI transactions and loan disbursement. To this end, we obtain 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 and can track 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 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:

$$Y_{it} = \alpha_{s(i)t} + \beta \times \mathrm{X} + \epsilon_{it} \tag{7}$$

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 7 presents the results. The descriptive statistics in Panel A suggest similar, though slightly higher mean exposure of 0.69 relative to the baseline exposure mean of 0.60. 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.[22] Overall, these results are consistent with the idea that lenders are incorporating a digital

[22] For robustness, in Internet Appendix Table IA13 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.

income trail created by UPI in their credit decisions.

6 Additional tests

6.1 Impact on default

Does the greater access to loans translate to higher default rates? We test for differences in default in different credit categories across regions that are more and less exposed to the new UPI technology. Panel A of Table 8 reports the aggregate univariate statistics on default rates. Despite the relatively larger increase in credit to marginal borrowers, we find no statistically significant differential increase in default rates in high-exposure pincodes (column 7). We turn to multivariate regressions in Panel B, Table 8, to control 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.

6.2 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; Agarwal et al., 2024), 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 a sharp uptick in UPI and fintech credit after September 2017 (see Figure 5 and discussion in Section 4), 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.

Nonetheless, for robustness, we provide additional evidence to rule out these concerns. Although direct cash shortage is difficult to measure, we obtain data on the distance to the nearest currency chest, which is a good proxy for cash availability during the demonetization episode (Chodorow-Reich et al., 2020). 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 good proxy for cash availability during the period.

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 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-quarter 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 regarding the demonetization episode driving our results, further strengthening the causal interpretation of our findings.

7 Conclusion

Nearly 850 million individuals in India are credit unserved or under-served. A first-order question in financial inclusion is: how do we expand credit access to the marginal population? This paper investigates whether digital public payment infrastructure coupled with Open Banking can enable credit access. We use a difference-in-differences empirical design that exploits regional variation in exposure to the Open-banking based digital payment infrastructure (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 by both banks and fintechs, along both intensive and extensive margins, and across various borrower profiles. 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. Finally, our findings underscore that digital payments and Open Banking are highly effective in facilitating access to formal credit by complementing first-time bank accounts for those who were previously excluded from these markets.

The results of this study inform not just academicians but also help move the debate forward with policymakers. As countries debate Open Banking and the role that governments should take, knowing the results of a large-scale experiment adopted in

India where Open Banking and public investment in digital infrastructure were taken is important. Had these measures failed or produced little effect, arguing for reforms towards even a subset of these measures would be hard to justify. Given the success of Open Banking combined with the public provision of digital payment infrastructure in providing access to credit, the next question would be if partial movement towards these, e.g., limited Open Banking as proposed in many countries, with private digital payments would still have aggregate effects. These are important questions for further research.

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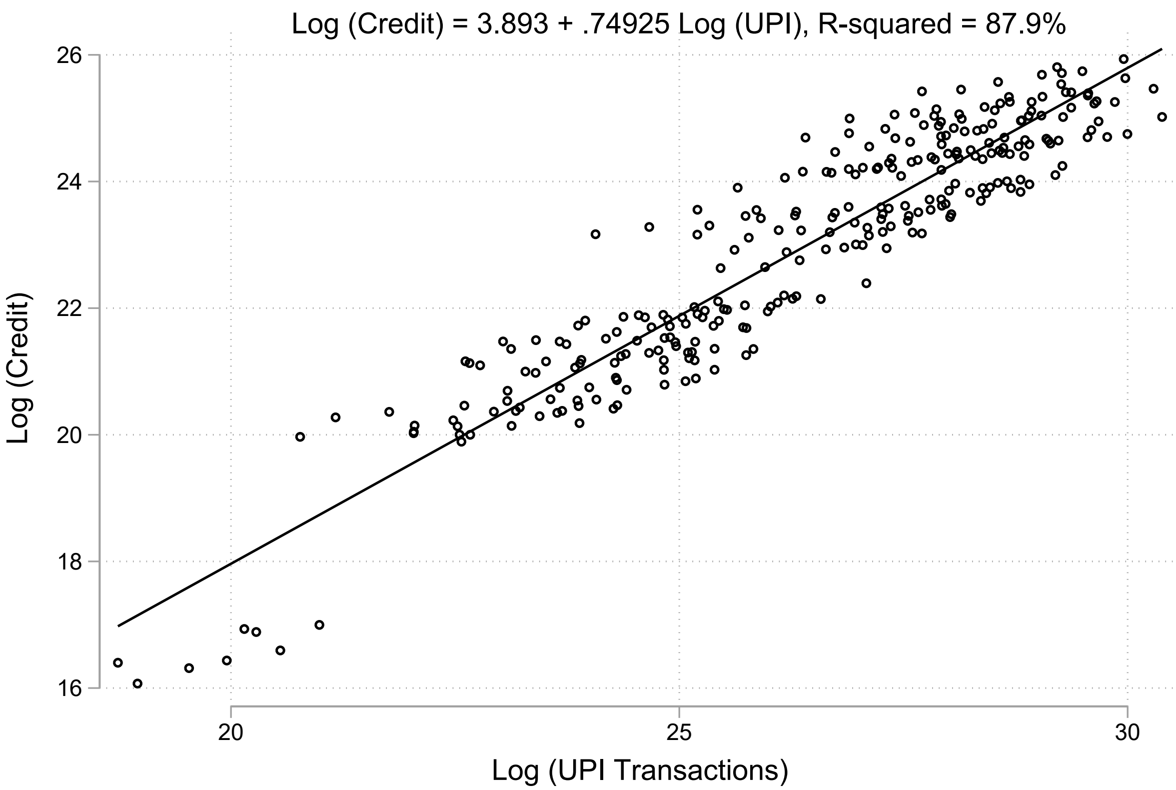
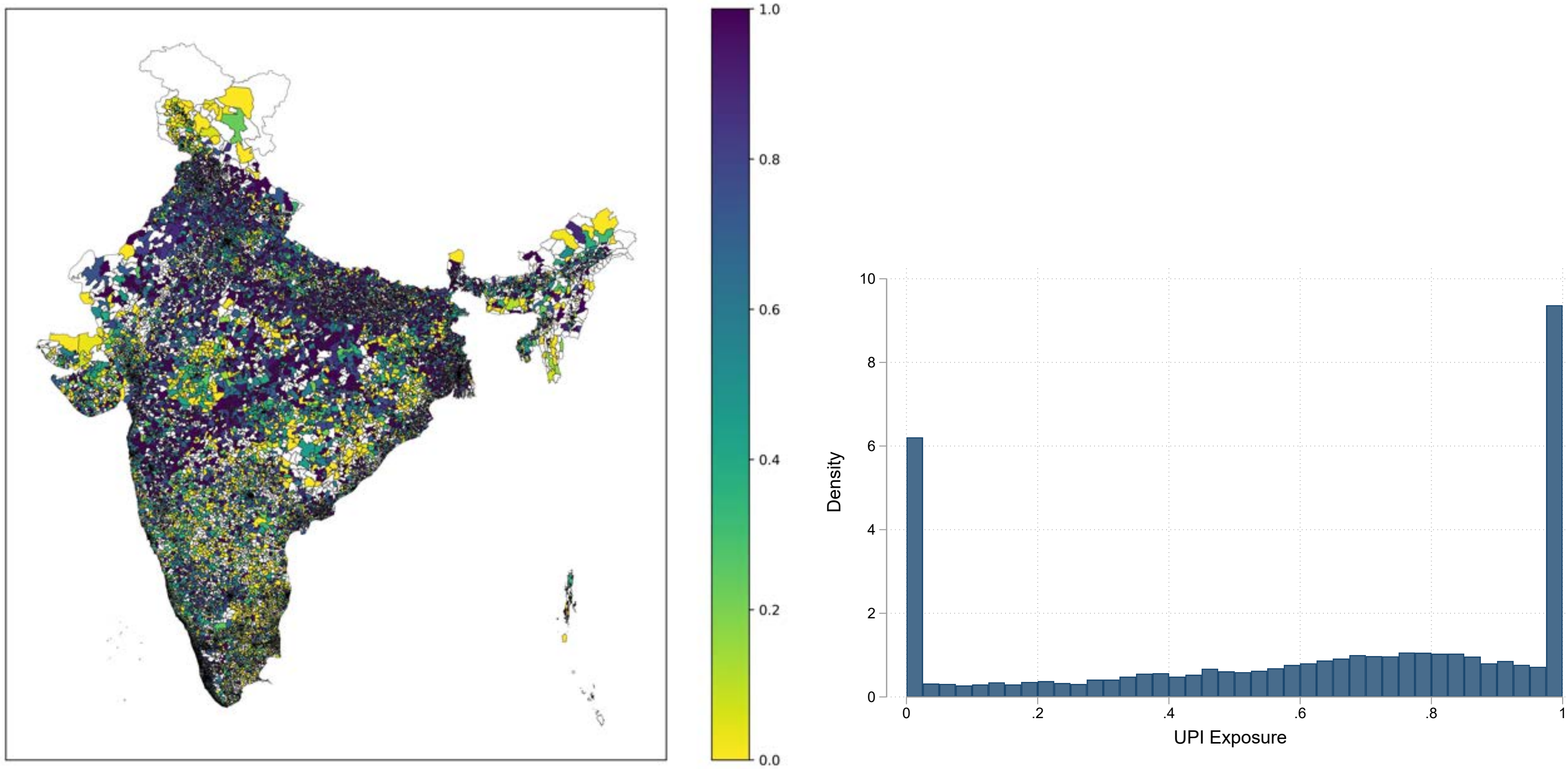
Figure 1
Aggregate Relationship Between UPI and Credit



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-month observation. The blue line is the line of best fit. The text above the graph shows the estimated regression specification for the line of best fit.

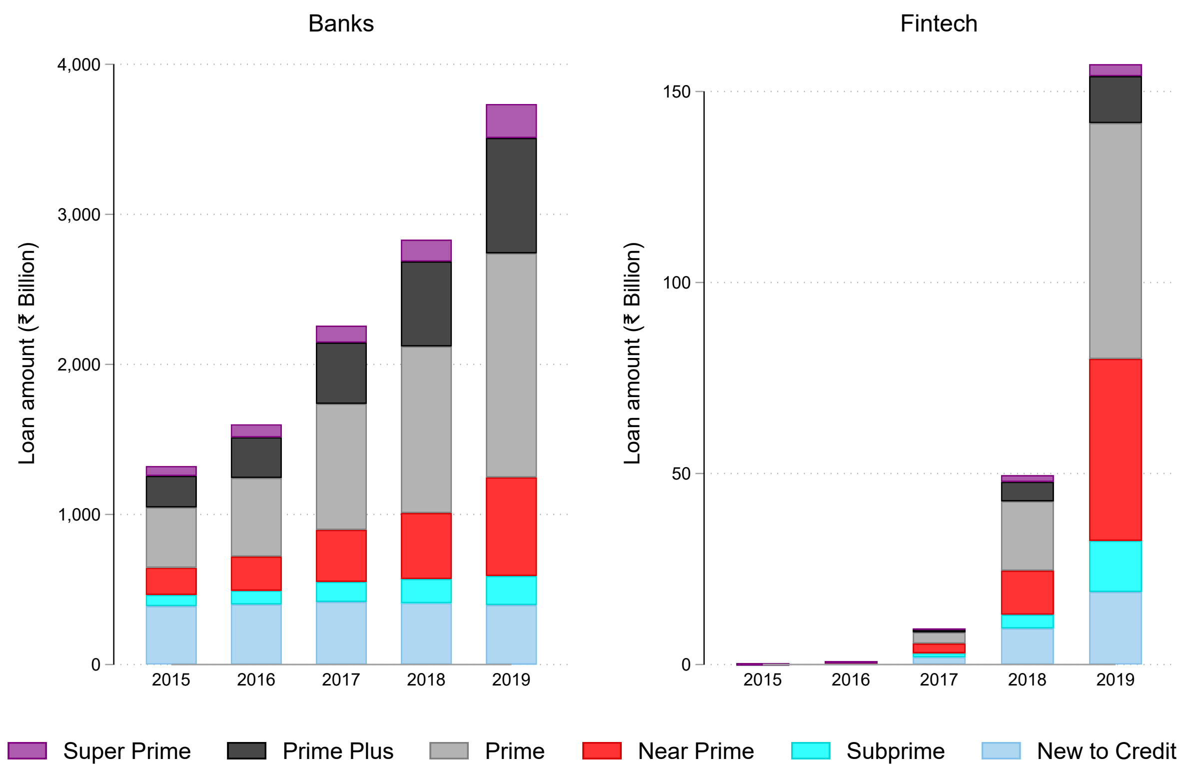
Figure 2
Variation in UPI Exposure



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

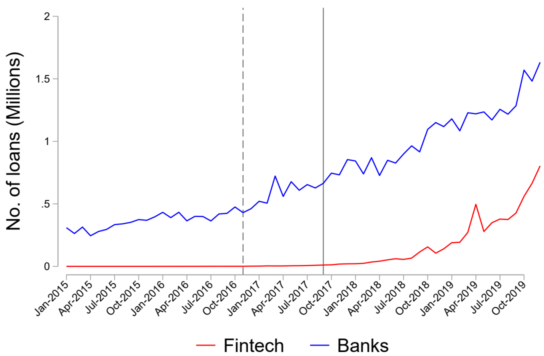
Notes: his figure shows the variation in value of UPI exposure across pincodes. Exposure measure is defined as the ratio of deposits for early adopter banks to total deposits as defined in Equation (1). UPI Expsure is bounded between 0 and 1. Panel A shows the variation on a map, with darker shades corresponding 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 November 2016. Deposit data is from Basic Statistical Returns (BSR) provided by the Reserve Bank of India.

Figure 3
Credit Composition by Lender

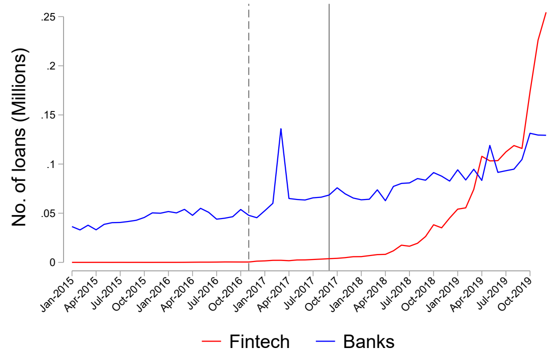


Notes: This figure shows the trends and composition of loan value (₹billion) by Banks and Fintechs, respectively. For each of these lenders, each stacked colored bar represents the credit score band, ranging from Super Prime at the top to New to Credit at the bottom. The trends cover the period 2015-2019.

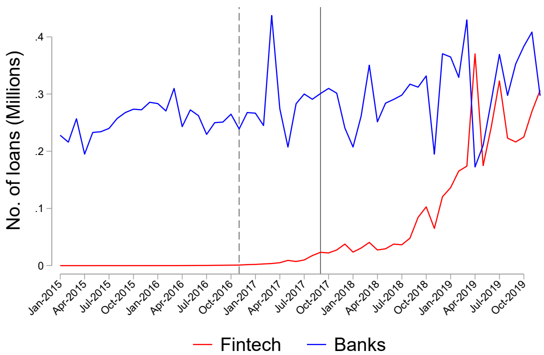
Figure 4
Trends in Credit by Lender



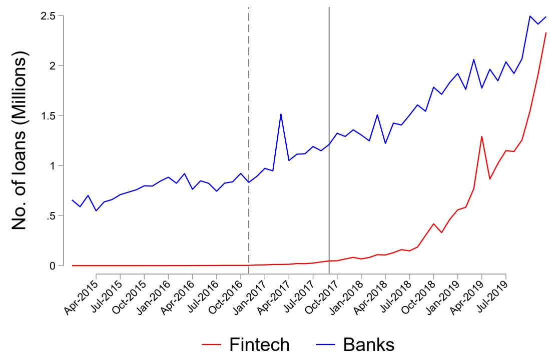
Panel A: Prime



Panel B: Subprime



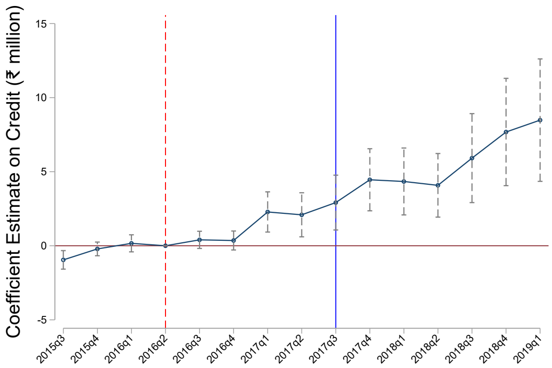
Panel C: New-to-credit



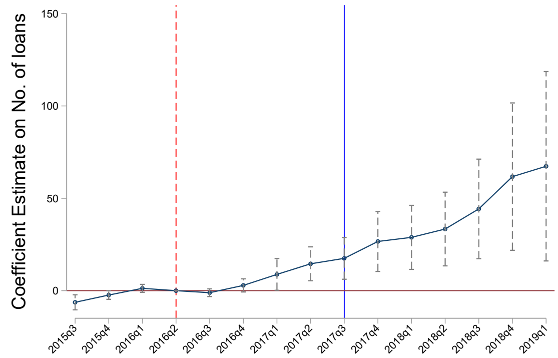
Panel D: All

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 (Panel 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 January 2015 to December 2019. The dashed vertical line marks the demonetization month (November 2016), while the solid grey line marks September 2017, when a circular released by the Reserve Bank of India strengthened the open banking system.

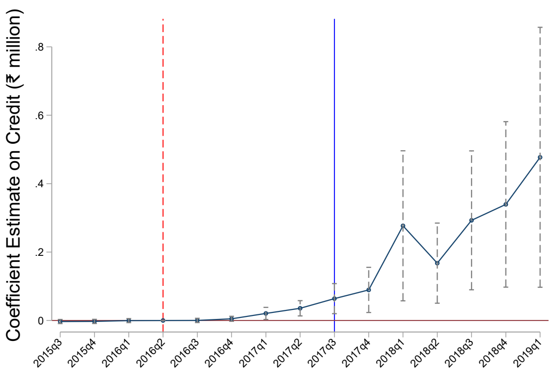
Figure 5
Treatment Dynamics: Impact on Credit



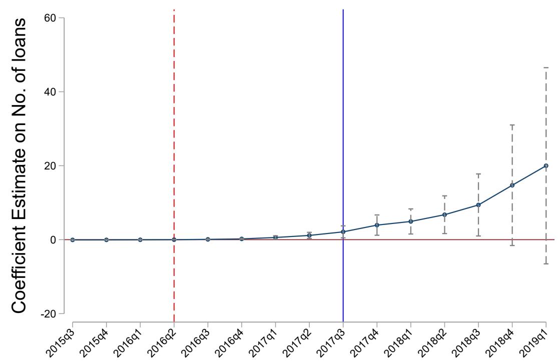
Panel A: Total loan amount



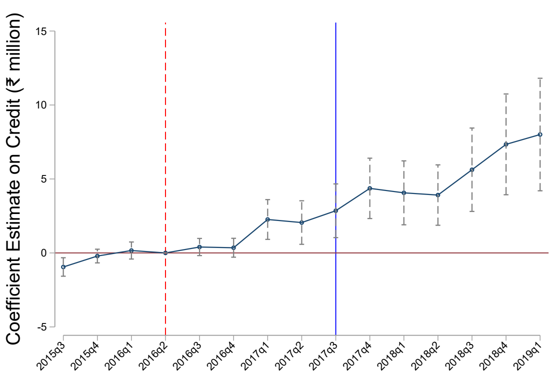
Panel A: Total number of loans



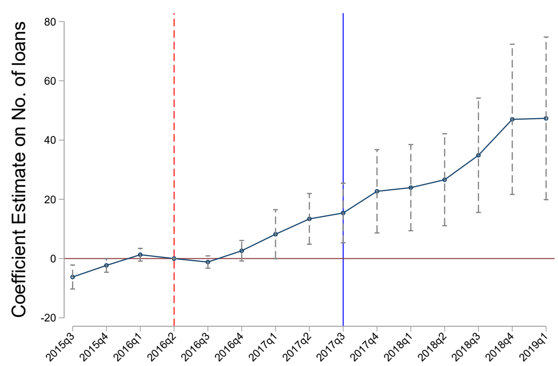
Panel C: Fintech loan amount



Panel D: Fintech number of loans



Panel C: Bank loan amount

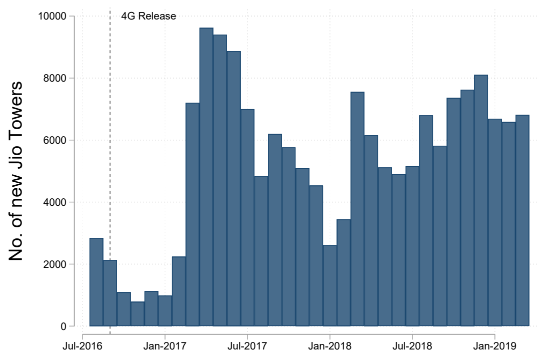


Panel C: Bank number of loans

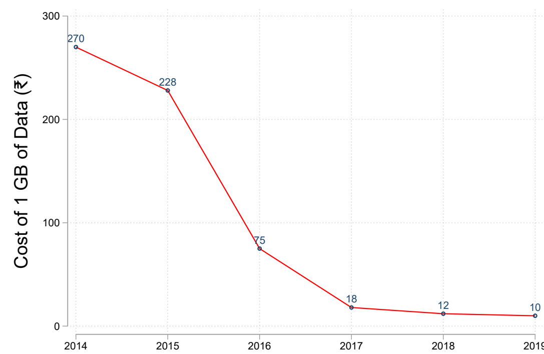
Notes: This figure shows the treatment dynamics using the specification in Equation (4) for total (Panel A), Fintech (Panel B) and Bank credit (Panel C). The dependent variables are loan value (in ₹million) and number of loans. Underlying observations are at the pincode level at the quarterly frequency for the period Q3 2015 to Q1 2019. Each point on the navy line shows the point estimate. The grey dotted lines indicate the 95% confidence intervals. Pincode and district-quarter fixed effects are included. Standard errors are heteroskedasticity robust and clustered at the pincode level. The dashed red line marks the pre-treatment quarter (Q2 2016), and the solid blue line marks September 2017, when a circular released by the Reserve Bank of India strengthened the open banking system.

Figure 6
The Jio Revolution

Panel A: New towers



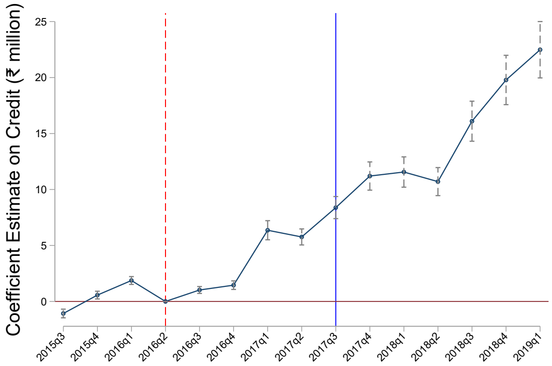
Panel B: Falling data costs



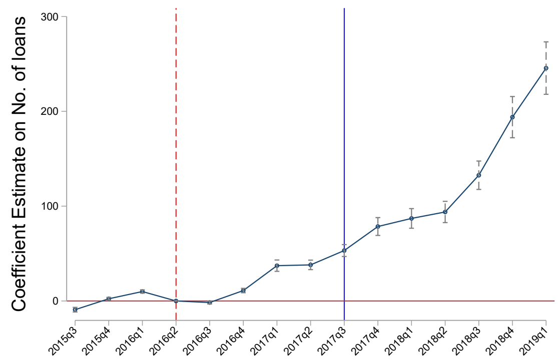
Panel C: Distance to Jio Tower

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 2019 (right map). Each blue point represents an active Jio tower.

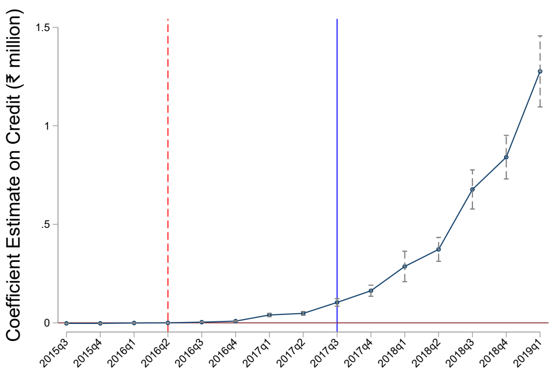
Figure 7
Treatment Dynamics: Impact of Jio



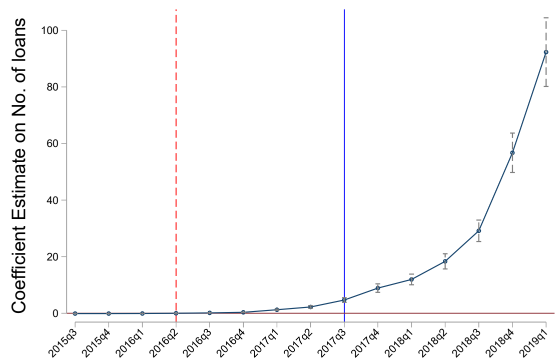
Panel A: Total loan amount



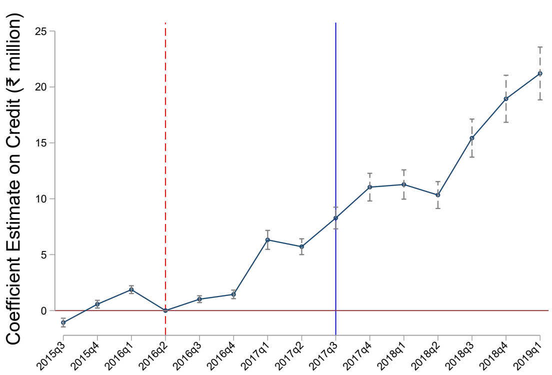
Panel B: Total number of loans



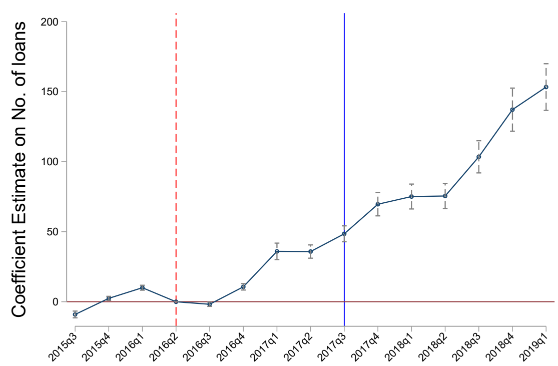
Panel C: Fintech loan amount



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 for total (Panel A), Fintech (Panel B) and Bank credit (Panel C), 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 quarterly frequency for the period Q3 2015 to Q1 2019. Each point on the navy line shows the point estimate. The grey dotted lines indicate the 95% confidence intervals. Pincode and district-quarter fixed effects are included. Standard errors are heteroskedasticity robust and clustered at the pincode level. The dashed red line marks the pre-treatment quarter (Q2 2016), and the solid blue line marks September 2017, when a circular released by the Reserve Bank of India strengthened the open banking system.

Table 1
Summary Statistics

	Mean	Median	St. Dev
UPI Exposure (N=12,493)	0.60	0.69	0.36
UPI			
UPI Transactions (Value: ₹million)	32.15	7.95	74.18
UPI Transactions (Volume in 1000s)	14.15	3.96	30.37
Credit			
Total Loan Amount (₹million)	41.63	11.19	128.37
Total no. of loans	289.68	64.00	979.52
By Score Band			
Subprime Loan Amount (₹million)	2.38	0.60	7.17
Subprime no. of loans	17.00	4.00	61.41
New-to-credit Loan Amount (₹million)	7.66	2.87	17.88
New-to-credit no. of loans	70.12	20.00	201.95
By Lender			
Fintech Loan Amount (₹million)	0.44	0.00	3.70
Fintech no. of loans	24.19	0.00	193.05
Banks Loan Amount (₹million)	41.19	11.13	125.89
Banks no. of loans	265.50	60.00	852.56
N (pincode × quarter)		187,395	

Notes: This table presents the summary statistics for the pincode-quarter 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 Q3 2015 to Q1 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	0.01	7.563	7.553***	0.022	9.918	9.896***	2.343***
Subprime	0.010	2.765	2.756***	0.018	3.594	3.577***	0.821***
Prime	0.014	8.217	8.202***	0.024	10.581	10.557***	2.355***
				Panel B: Banks			
New-to-credit	51.079	54.008	2.929***	69.842	75.763	5.921***	2.992
Subprime	9.771	15.078	5.307***	12.116	16.9661	4.850***	-0.457
Prime	45.429	93.332	47.903***	58.809	125.481	66.672***	18.77***

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

Notes: This table shows the mean number of loans granted at the pin code-quarter 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 Q3 2015 to Q1 2019. Pre refers to the period before Q3 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		New-to-credit		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High Exposure × Post	4.159***	29.558***	0.135***	1.167**	-0.045	2.252**	3.356***	20.943***
	(1.072)	(9.672)	(0.049)	(0.556)	(0.051)	(1.083)	(0.850)	(6.217)
R^2	0.938	0.885	0.902	0.835	0.964	0.942	0.915	0.876
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	28.323	182.802	1.652	10.971	7.651	60.515	15.101	86.761
Post-UPI Mean	46.468	329.071	2.644	19.201	7.637	73.681	28.993	183.065
Dep. var mean	41.630	290.066	2.379	17.007	7.641	70.170	25.288	157.384
N	186,900	186,900	186,900	186,900	186,900	186,900	186,900	186,900

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. Observations are at the pincode-quarter level and span the period Q3 2015 to Q1 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 Q3 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 Exposure × Post	0.162***	5.832**	3.997***	23.711***
	(0.055)	(2.970)	(1.022)	(7.089)
R^2	0.525	0.452	0.942	0.934
Pre-UPI Mean	0.004	0.076	28.319	182.726
Post-UPI Mean	0.607	33.069	45.862	296.040
Dep. var mean	0.446	24.271	41.184	265.823
	Panel B: Subprime sample			
High Exposure × Post	0.012**	0.552*	0.124***	0.614**
	(0.005)	(0.301)	(0.046)	(0.279)
R^2	0.561	0.467	0.904	0.892
Pre-UPI Mean	0.001	0.014	1.652	10.957
Post-UPI Mean	0.048	3.191	2.596	16.014
Dep. var mean	0.035	2.344	2.344	14.666
	Panel C: New-to-credit sample			
High Exposure × Post	0.028***	1.629**	-0.073	0.618
	(0.008)	(0.714)	(0.052)	(0.595)
R^2	0.569	0.487	0.963	0.973
Pre-UPI Mean	0.001	0.016	7.650	60.499
Post-UPI Mean	0.110	8.769	7.527	64.922
Dep. var mean	0.081	6.435	7.560	63.743
	Panel D: Prime sample			
High Exposure × Post	0.088***	2.000**	3.268***	18.938***
	(0.029)	(1.013)	(0.824)	(5.348)
R^2	0.439	0.449	0.919	0.904
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.029	15.099	86.732
Post-UPI Mean	0.300	11.296	28.693	171.782
Dep. var mean	0.221	8.291	25.068	149.102
N	186,690	186,690	186,900	186,900

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-quarter level and span the period Q3 2015 to Q1 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 Q3 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 5
Mechanism: Financial Formalization

	(1)	(2)	(3)	(4)	(5)	(6)
Lender	All		Fintech		New-to-credit & Fintech	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act per capita	Amt (₹million)	Act
High Exposure × High JDY × Post	4.943***	42.503***	0.169**	6.712*	0.036***	2.175**
	(1.510)	(13.664)	(0.078)	(4.059)	(0.012)	(0.982)
High Exposure × Post	0.956	2.130	0.053	1.379	0.005	0.216
	(0.723)	(6.441)	(0.041)	(1.675)	(0.006)	(0.435)
High JDY × Post	14.266***	114.887***	0.470***	27.600***	0.077***	6.779***
	(0.980)	(9.275)	(0.051)	(2.878)	(0.008)	(0.683)
R^2	0.938	0.886	0.526	0.453	0.570	0.489
Pincode FE	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	28.323	182.802	0.004	0.076	0.001	0.016
Post-UPI Mean	46.468	329.071	0.607	33.069	0.110	8.769
Dep. var mean	41.630	290.066	0.446	24.271	0.081	6.435
N	186,900	186,900	186,690	186,690	186,690	186,690

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 a new-to-credit loans (columns 5-6), at quarterly frequency for the period Q3 2015 to Q1 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 Q3 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table 6
Mechanism: Connectivity With Jio

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All		New-to-credit		All	
Dependent var.	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act Act
	Panel A: Fintechs					
$\text{Early}_{\text{Jio}} \times$ High Exp. $\times$ Post	0.245***	7.774*	0.039***	1.972**	0.228***	6.904*
	(0.078)	(4.160)	(0.012)	(0.993)	(0.074)	(3.965)
High Exp. $\times$ Post	0.008	0.772	0.003	0.348	-0.012	-0.051
	(0.025)	(1.280)	(0.004)	(0.328)	(0.017)	(0.909)
$\text{Early}_{\text{Jio}} \times$ Post	0.226***	16.709***	0.041***	4.156***	0.287***	20.486***
	(0.039)	(2.227)	(0.006)	(0.542)	(0.039)	(2.231)
$\text{High}_{\text{Non-Jio}} \times$ High Exp. $\times$ Post					0.048*	2.259
					(0.029)	(1.575)
$\text{High}_{\text{Non-Jio}} \times$ Post					-0.296***	-18.392***
					(0.025)	(1.317)
R^2	0.525	0.453	0.570	0.488	0.526	0.453
Pre-UPI Mean	0.004	0.076	0.001	0.016	0.004	0.076
Post-UPI Mean	0.606	33.039	0.110	8.761	0.606	33.039
Dep. var mean	0.444	24.187	0.080	6.414	0.444	24.187
N	186,855	186,855	186,855	186,855	186,855	186,855
	Panel B: Banks					
$\text{Early}_{\text{Jio}} \times$ High Exp. $\times$ Post	5.282***	39.324***	0.126	2.711***	4.884***	36.832***
	(1.454)	(10.471)	(0.090)	(0.908)	(1.388)	(10.019)
High Exp. $\times$ Post	0.628	-1.265	-0.144***	-1.044**	0.058	-4.395
	(0.575)	(3.882)	(0.051)	(0.420)	(0.474)	(3.281)
$\text{Early}_{\text{Jio}} \times$ Post	7.090***	47.049***	-0.344***	-0.062	7.956***	54.366***
	(0.788)	(5.811)	(0.068)	(0.523)	(0.785)	(5.764)
$\text{Early}_{\text{Non-Jio}} \times$ High Exp. $\times$ Post					1.259**	7.367*
					(0.523)	(3.793)
$\text{Early}_{\text{Non-Jio}} \times$ Post					-4.055***	-34.976***
					(0.415)	(3.131)
R^2	0.942	0.935	0.963	0.973	0.942	0.935
Pincode FE	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	28.320	182.502	7.662	60.459	28.320	182.502
Post-UPI Mean	45.862	296.040	7.527	64.922	45.862	296.040
Dep. var mean	41.188	265.497	7.576	63.705	41.188	265.497
N	186,900	186,900	186,900	186,900	186,900	186,900

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. Columns 5–6 include the triple difference estimates for the differential impact of UPI exposure on credit in pincodes with early access to a Reliance Jio tower with those with proximity to a non-Jio tower for all loans. Observations are at the pincode level at quarterly frequency for Q3 2015–Q1 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). $\text{Early}_{\text{Jio}}$ ($\text{Early}_{\text{Non-Jio}}$) takes a value 1 when a pincode's distance to an active 4G Jio (Non-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 7
Digital Verifiability of Revenues: Evidence From a Large Fintech Lender

Panel A: Summary statistics

Variable	Mean	St. Dev.	p25	p50	p75
UPI					
High Exposure (0 to 1)	0.69	0.23	0.59	0.73	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 Var.	Loan Size (in 000's)		Interest Rate (in %)		Internal Credit Score Dummy		Internal Credit Score Cont.	
Log(QR-UPI Val.)	34.695***		-0.023***		0.010***		1.533***	
	(0.871)		(0.001)		(0.001)		(0.033)	
Log(QR-UPI #)		27.904***		-0.019***		0.011***		1.314***
		(0.689)		(0.001)		(0.001)		(0.031)
R^2	0.166	0.140	0.106	0.104	0.933	0.933	0.239	0.224
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	39,602	39,602	39,602	39,602	39,602	39,602	18,973	18,973

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 8
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	0.056	0.0860	0.030***	0.064	0.087	0.023	-0.007
Subprime	0.115	0.113	-0.002	0.139	0.111	-0.027	0.026
Prime	0.019	0.052	0.033***	0.024	0.052	0.029***	0.004
Banks							
New-to-credit	0.015	0.031	0.016***	0.016	0.032	0.016***	-.002
Subprime	0.039	0.062	0.023***	0.036	0.060	0.024***	-0.0005
Prime	0.010	0.024	0.014***	0.011	0.024	0.014***	0.001*

Panel B: Impact on default rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Default Rate							
Lender	Fintech				Banks			
Score Band	All	New-to-credit	Sub-prime	Prime	All	New-to-credit	Sub-prime	Prime
High Exp. × Post	-0.000	-0.021	0.006	-0.002	-0.000	0.000	-0.000	0.001
	(0.009)	(0.018)	(0.044)	(0.010)	(0.000)	(0.001)	(0.002)	(0.000)
R^2	0.302	0.340	0.399	0.334	0.327	0.201	0.207	0.221
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.049	0.051	0.119	0.023	0.015	0.016	0.038	0.011
Post-UPI Mean	0.077	0.086	0.111	0.051	0.030	0.031	0.061	0.024
Dep. var mean	0.076	0.086	0.111	0.051	0.026	0.027	0.056	0.021
N	78,510	60,330	35,823	56,963	186,721	185,493	158,346	185,913

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

Notes: This table shows the mean default rate at the pincode-quarter 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-quarter. High and low exposure correspond to dummy variable that identifies pincodes with above/below median exposure, defined as in Equation (1). Data is for the period Q3 2015 to Q1 2019. Pre refers the period before Q3 2016 and Post thereafter. 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 Q3 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Appendix

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
Nightlight Intensity per capita	6,243	0.001 (0.000)	6,246	0.001 (0.000)	12,489	-0.000
Nightlight per capita (Growth)	6,240	0.075 (0.013)	6,238	0.077 (0.004)	12,478	-0.001
Credit per capita	6,243	819.981 (93.844)	6,246	643.127 (67.265)	12,489	176.854
Growth in credit per capita	6,242	0.159 (0.003)	6,243	0.153 (0.003)	12,485	0.007
Subprime & new-to-credit loan share per capita	6,243	0.000 (0.000)	6,246	0.000 (0.000)	12,489	-0.000
Growth in subprime & new-to-credit loan share per capita	6,240	0.098 (0.004)	6,239	0.105 (0.004)	12,479	-0.008

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

	(1)	(2)
Dependent variable	UPI value (₹million)	UPI volume (in 000s)
High Exposure	4.092*** (1.058)	1.701*** (0.426)
R^2	0.413	0.438
District-quarter FE	Y	Y
Dep. var mean	32.218	14.187
N	84,708	84,708

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-quarter level and span the period Q3 2015 to Q1 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

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

Panel B: Determinants of Jio Entry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	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

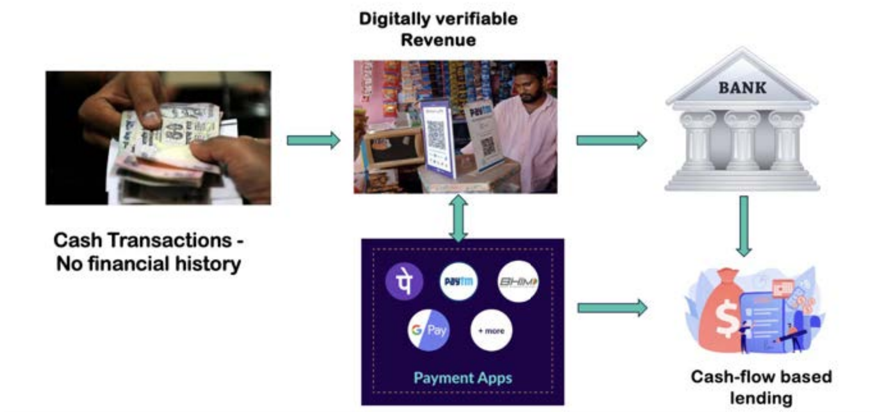
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Score Band	All		Subprime		New-to-credit		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High Exposure × Post	4.218***	30.044***	0.138***	1.193**	-0.045	2.296**	3.402***	21.261***
	(1.071)	(9.670)	(0.049)	(0.556)	(0.051)	(1.085)	(0.849)	(6.212)
R^2	0.938	0.885	0.902	0.835	0.964	0.942	0.916	0.876
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
$\text{Dist}_{CC}\times$ Quarter Control	Y	Y	Y	Y	Y	Y	Y	Y
Dep. var mean	41.630	290.066	2.379	17.007	7.641	70.170	25.288	157.384
N	186,900	186,900	186,900	186,900	186,900	186,900	186,900	186,900

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 quarterly frequency for the period Q3 2015 to Q1 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 Q3 2016 onwards. Pincode and Fixed effects are included as indicated. Dist_{CC} × Quarter Control is the interaction of the distance of a pincode to the nearest currency chest and quarter t. Pincode clustered standard errors are reported in parantheses.

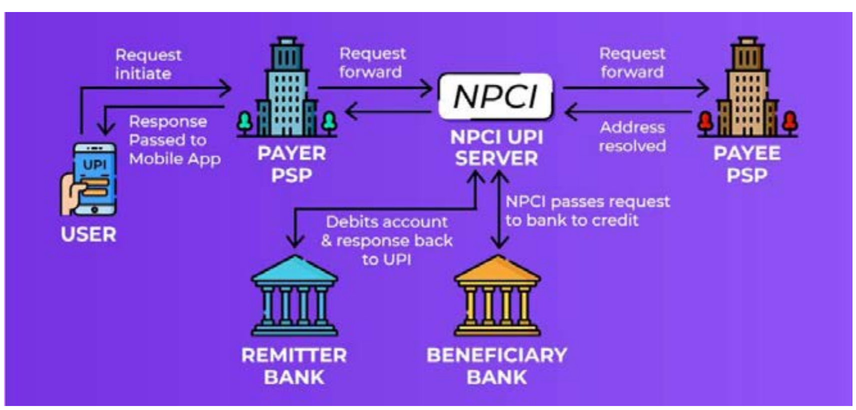
Internet Appendix

Figure IA1
UPI and Credit: Schematic Diagram



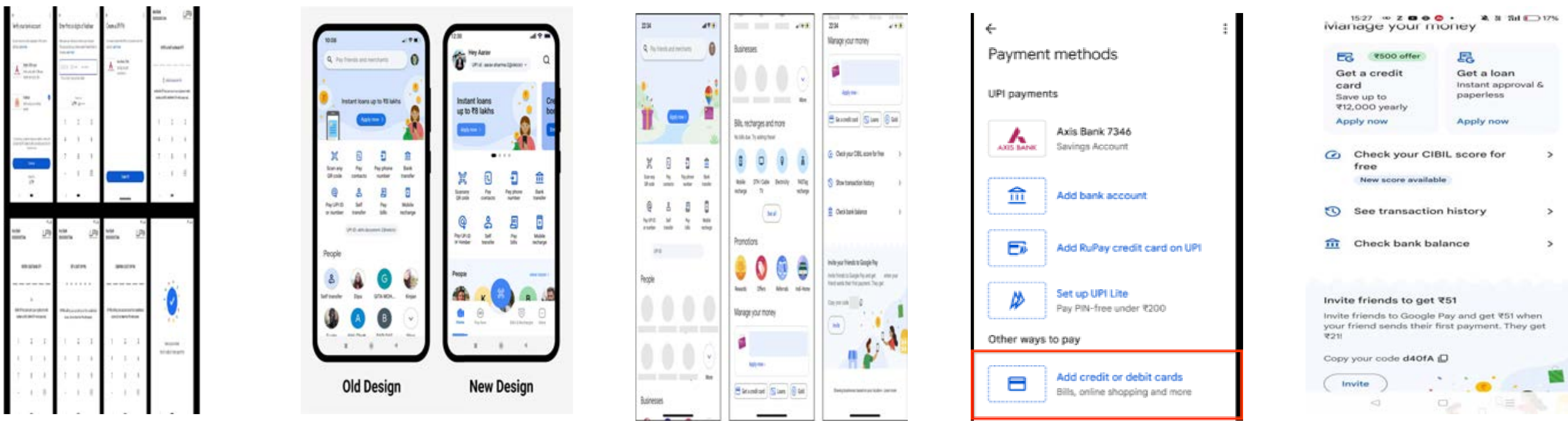
*Notes:*This figure is a schematic representation of how the introduction of an open banking digital platform (UPI) leads to an increased disbursal of credit. The leftmost box refers to a pre-open banking stage, where most transactions occur in cash, leading to a lack of documented history. Introducing 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

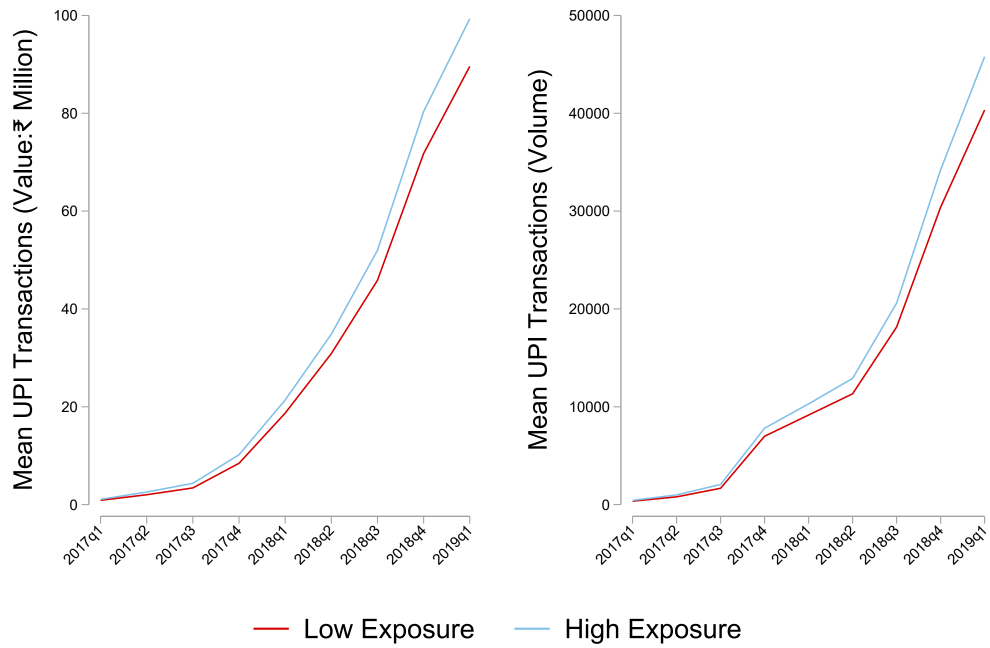
Figure IA3
UPI Loan Application Navigation Page



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

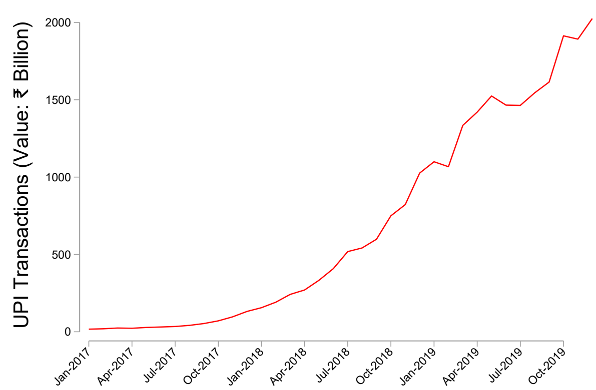
Notes: This figure shows the various stages of navigating UPI as a payment system. It begins with the process of account opening (Panel A), an illustrative landing page (Panel B), the interface of a payment system called Google Pay (Panel C), the various payment methods available (Panel D), and the option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

Figure IA4
Trends in UPI Transactions by Exposure



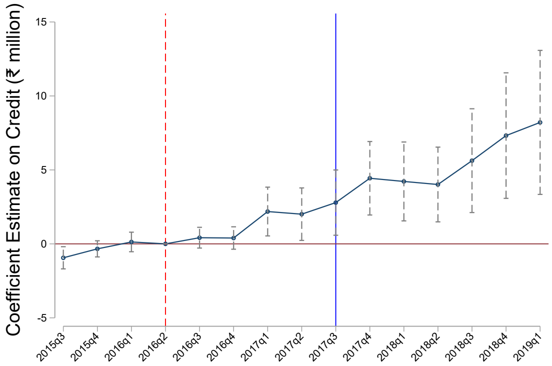
Notes: This figure shows the mean value of UPI Transactions (in ₹million) and mean number of UPI Transactions for low UPI exposure pincodes (red line) and high UPI exposure pincodes (blue line). The data is at a quarterly frequency and covers the period 2017Q1 to 2019Q1

Figure IA5
Trends in UPI Transactions

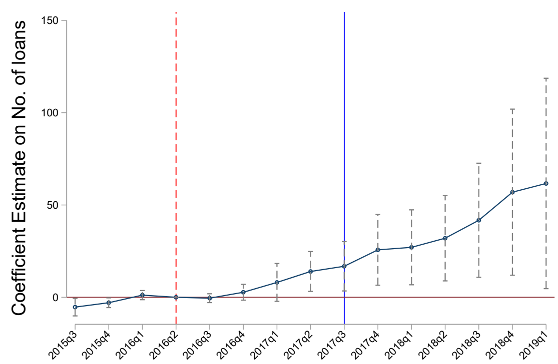


Notes: 'This figure presents the aggregate trends in the value of UPI transactions over the period January 2017 to December 2019. The unit of transactions is ₹billion.

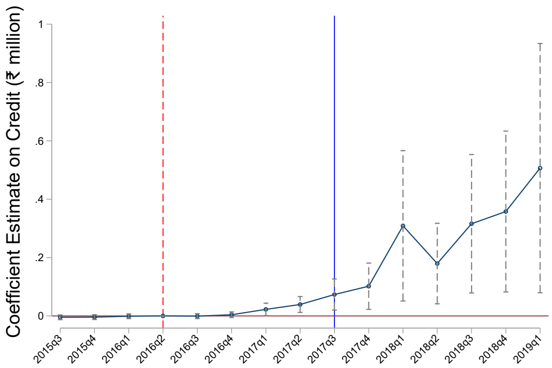
Figure IA6
Robustness With Grid Fixed Effect: Treatment Dynamics for the Impact on Credit



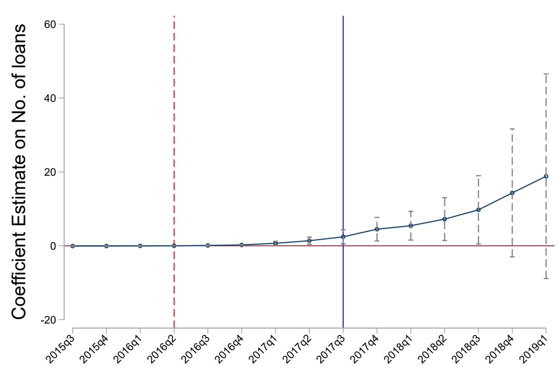
Panel A: Total loan amount



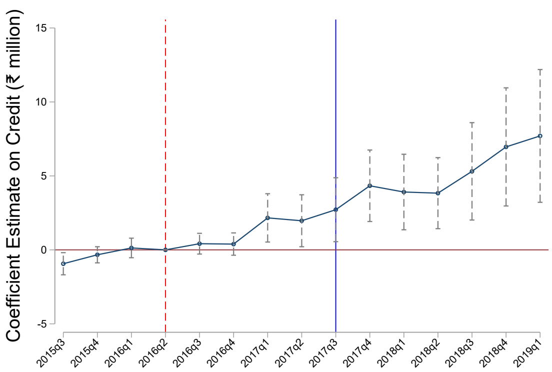
Panel B: Total number of loans



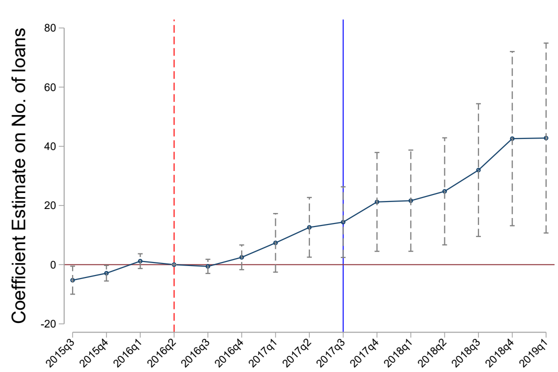
Panel C: Fintech loan amount



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 (Panel A), Fintech (Panel B) and Bank credit (Panel C). The dependent variables are loan value (₹million) and number of loans. Underlying observations are at the pincode level at the quarterly frequency for the period Q3 2015 to Q1 2019. Each point on the navy line shows the point estimate. The grey dotted lines indicate the 95% confidence intervals. Fixed effects are included as indicated. The dashed red line marks the pre-treatment quarter (Q2 2016), and the solid blue line marks September 2017, when a circular released by the Reserve Bank of India strengthened the open banking system.

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)						
	Low Exposure			High Exposure			DiD
	Pre	Post	Post-Pre	Pre	Post	Post-Pre	High-Low
	Panel A: Fintech						
New-to-credit	0.001	0.090	0.090***	0.009	0.129	0.127***	0.037***
Subprime	0.000	0.039	0.039***	0.001	0.056	0.055***	0.016***
Prime	0.001	0.241	0.240***	0.002	0.357	0.354***	0.114***
	Panel B: Banks						
New-to-credit	6.718	6.439	-0.279***	8.606	8.650	0.044	0.322*
Subprime	1.588	2.562	0.974***	1.715	2.636	0.921***	-0.053
Prime	13.141	24.813	11.672***	17.039	32.55	15.551***	3.839***

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

Notes: This table shows the mean loan amount (₹million) at the pin code-quarter 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 Q3 2015 to Q1 2019. Pre refers to the period before Q3 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.	Act.	Val.	Act.	Val.	Act.
All Credit	0.15	0.16	0.08	0.11	-	0.04
Fintech Lenders	40.5	77	120.0	39.4	28	101.8
Banks	0.14	0.13	0.08	0.06	-	-

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 with Grid Fixed Effects: Impact on UPI

	(1)	(2)
Dependent variable	UPI value (₹million)	UPI volume (in 000s)
High Exposure	3.283***	1.391***
	(1.249)	(0.497)
R^2	0.488	0.514
District-quarter FE	Y	Y
Grid quarter FE	Y	Y
Dep. var mean	32.298	14.218
N	82,287	82,287

Notes: This table presents the OLS estimates for the impact of exposure on UPI transactions. Observations are at the pincode level at quarterly frequency for the period Q3 2015 to Q1 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 with Grid Fixed Effects: Impact on Credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score Band	All		Subprime		New-to-credit		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High Exposure × Post	4.051***	27.631**	0.124**	1.119*	-0.040	2.362*	3.267***	19.198***
	(1.273)	(11.166)	(0.057)	(0.626)	(0.058)	(1.222)	(1.012)	(7.260)
R^2	0.943	0.896	0.908	0.860	0.967	0.947	0.922	0.888
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	28.464	184.442	1.654	11.064	7.644	60.912	15.223	87.674
Post-UPI Mean	46.713	332.338	2.638	19.337	7.629	74.219	29.214	185.117
Dep. var mean	41.846	292.899	2.376	17.131	7.633	70.671	25.483	159.132
N	183,750	183,750	183,750	183,750	183,750	183,750	183,750	183,750

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 quarterly frequency for the period Q3 2015 to Q1 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 Q3 2016 onwards. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.

Table IA6

Robustness With 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 Exposure × Post	0.174***	5.842*	3.877***	21.759***
	(0.064)	(3.222)	(1.215)	(8.343)
R^2	0.557	0.502	0.947	0.941
Pre-UPI Mean	0.004	0.078	28.460	184.364
Post-UPI Mean	0.615	33.451	46.098	298.931
Dep. var mean	0.452	24.551	41.395	268.380
	Panel B: Subprime sample			
High Exposure × Post	0.013**	0.566*	0.111**	0.551*
	(0.005)	(0.329)	(0.053)	(0.325)
R^2	0.589	0.512	0.910	0.918
Pre-UPI Mean	0.001	0.014	1.654	11.050
Post-UPI Mean	0.048	3.231	2.590	16.110
Dep. var mean	0.036	2.373	2.340	14.761
	Panel C: New-to-credit sample			
High Exposure × Post	0.030***	1.705**	-0.071	0.647
	(0.010)	(0.779)	(0.059)	(0.699)
R^2	0.602	0.533	0.966	0.976
Pre-UPI Mean	0.001	0.016	7.643	60.895
Post-UPI Mean	0.111	8.849	7.518	65.382
Dep. var mean	0.082	6.493	7.552	64.186
	Panel D: Prime sample			
High Exposure × Post	0.093***	1.938*	3.173***	17.250***
	(0.034)	(1.108)	(0.982)	(6.295)
R^2	0.470	0.500	0.925	0.914
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.029	15.221	87.645
Post-UPI Mean	0.305	11.443	28.910	173.689
Dep. var mean	0.224	8.399	25.260	150.744
N	183,510	183,510	183,750	183,750

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-quarter level and span the period Q3 2015 to Q1 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 Q3 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)	UPI volume (in 1000s)
High Exposure	17.540***	7.063***
	(1.532)	(0.604)
R^2	0.689	0.692
Pair-time FE	Y	Y
Dep. var mean	36.824	15.924
N	61236	61236

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		New-to-credit		Prime	
Dependent variable	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act	Amt (₹million)	Act
High Exposure × Post	12.843***	92.180***	0.595***	4.248***	-0.210***	5.360***	10.129***	65.191***
	(1.634)	(14.117)	(0.070)	(0.759)	(0.081)	(1.651)	(1.305)	(9.357)
R^2	0.972	0.947	0.962	0.932	0.991	0.975	0.961	0.941
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
Pair-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	35.490	234.503	1.954	13.847	9.418	77.437	19.232	111.861
Post-UPI Mean	58.574	424.443	3.084	23.623	9.459	94.861	37.035	237.903
Dep. var mean	52.418	373.792	2.783	21.016	9.448	90.215	32.288	204.292
N	160,530	160,530	160,530	160,530	160,530	160,530	160,530	160,530

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 quarterly frequency for the period Q3 2015 to Q1 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 Q3 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 Exposure × Post	0.409***	18.718***	12.434***	73.462***
	(0.080)	(3.248)	(1.561)	(11.188)
R^2	0.748	0.736	0.974	0.969
Pre-UPI Mean	0.006	0.106	35.484	234.397
Post-UPI Mean	0.810	42.283	57.764	382.160
Dep. var mean	0.595	31.036	51.823	342.757
	Panel B: Subprime sample			
High Exposure × Post	0.030***	1.782***	0.566***	2.466***
	(0.007)	(0.347)	(0.064)	(0.439)
R^2	0.784	0.742	0.964	0.970
Pre-UPI Mean	0.001	0.019	1.954	13.828
Post-UPI Mean	0.064	4.099	3.020	19.524
Dep. var mean	0.047	3.011	2.736	18.005
	Panel C: New-to-credit sample			
High Exposure × Post	0.068***	4.857***	-0.278***	0.503
	(0.012)	(0.786)	(0.083)	(1.110)
R^2	0.785	0.750	0.990	0.989
Pre-UPI Mean	0.001	0.023	9.416	77.414
Post-UPI Mean	0.143	11.152	9.316	83.709
Dep. var mean	0.105	8.184	9.343	82.030
	Panel D: Prime sample			
High Exposure × Post	0.220***	6.577***	9.909***	58.614***
	(0.045)	(1.131)	(1.267)	(8.336)
R^2	0.680	0.738	0.963	0.953
Pincode FE	Y	Y	Y	Y
Pair-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.003	0.040	19.230	111.821
Post-UPI Mean	0.406	14.452	36.630	223.452
Dep. var mean	0.298	10.609	31.990	193.683
N	160,530	160,530	160,530	160,530

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 C). Observations are at the pincode-quarter level and span the period Q3 2015 to Q1 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 Q3 2016 onwards. Fixed effects are included as indicated. Pincode clustered standard errors are reported in parantheses.

Table IA10

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 Exposure × Post	4.987***	33.375**	-0.003	2.834	0.035**	1.911
	(1.707)	(15.771)	(0.080)	(1.795)	(0.014)	(1.214)
R^2	0.942	0.892	0.967	0.946	0.603	0.512
Pre-UPI Mean	39.872	259.038	10.570	84.861	0.001	0.024
Post-UPI Mean	65.522	465.903	10.557	102.834	0.155	12.180
Dep. var mean	58.682	410.739	10.560	98.041	0.114	8.938
N	112,605	112,605	112,605	112,605	112,575	112,575
	Panel B: Low JDY					
High Exposure × Post	1.095***	9.467**	-0.010	0.334	0.006	0.319
	(0.418)	(3.821)	(0.039)	(0.553)	(0.004)	(0.292)
R^2	0.929	0.900	0.928	0.925	0.566	0.627
Pincode FE	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	10.668	66.987	3.136	23.381	0.000	0.004
Post-UPI Mean	17.353	121.442	3.131	29.297	0.042	3.590
Dep. var mean	15.570	106.921	3.132	27.719	0.031	2.634
N	72,900	72,900	72,900	72,900	72,885	72,885

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 early access to a Reliance Jio t 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 quarterly frequency for the period Q3 2015 to Q1 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 IA11
Impact on UPI by Connectivity with Jio

Dependent variable	(1) UPI value (₹million)	(2) UPI volume (in 000s)
$\text{Early}_{\text{Jio}}$	16.234***	6.550***
	(0.978)	(0.413)
R^2	0.420	0.445
District-quarter FE	Y	Y
Dep. var mean	32.218	14.187
N	84,708	84,708

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 quarterly frequency for the period Q1 2017 to Q1 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 IA12
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	0.248***	8.077	0.041***	2.189*	5.730***	35.834***	-0.076	1.314
	(0.095)	(5.087)	(0.014)	(1.215)	(1.709)	(12.147)	(0.084)	(0.998)
R^2	0.537	0.465	0.583	0.498	0.944	0.936	0.965	0.974
Post-UPI Mean	0.956	49.419	0.165	12.527	66.389	444.384	10.058	93.695
N	108,690	108,690	108,690	108,690	108,690	108,690	108,690	108,690
	Panel B: Late Jio							
High Exposure × Post	-0.017	-0.983	-0.002	-0.175	0.020	-2.469	-0.051	-0.453
	(0.010)	(0.660)	(0.002)	(0.186)	(0.347)	(2.146)	(0.046)	(0.347)
R^2	0.451	0.476	0.478	0.557	0.910	0.904	0.942	0.933
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.004	0.076	0.001	0.016	28.320	182.502	7.662	60.459
Post-UPI Mean	0.118	10.161	0.032	3.482	16.990	88.504	3.933	24.542
Dep. var mean	0.444	24.187	0.080	6.414	41.188	265.497	7.576	63.705
N	76,710	76,710	76,710	76,710	76,755	76,755	76,755	76,755

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 early access to a Reliance Jio t 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 quarterly frequency for the period Q3 2015 to Q1 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/Non-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 IA13

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-UPI T.Value)	39.731***		-0.030***		1.533***	
	(1.226)		(0.002)		(0.033)	
Log(QR-UPI 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	18,973	18,973	18,973	18,973	18,973	18,973

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 borrower-month of the loan level. Fixed effects are included as indicated. Pincode-clustered standard errors are reported in parentheses.