Cross-Platform Digital Payments and Customer-Driven Data Sharing: Implications for Credit Access

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Motivation

- 1.4 billion people around the world still lack bank accounts (World Bank 2022).
  - Even those with bank accounts lack credit access
  - Primarily due to the lack of credit history/credit score
- Promise of fintech - can use alternate data to create novel credit scoring models and expand credit access (See Berg, Burg, Gombovic, and Puri (2020), Agarwal, Alok, Ghosh and Gupta (2021))
  - However, little evidence that fintech firms in the US have delivered on this promise (Buchak,et al., 2018; Fuster et. al., 2019, Maggio et al 2021; Gopal et. al., 2022)
- **Our focus:** Can public digital payment infrastructure allowing cross-platform digital payments and consumer-driven data sharing help?

India's UPI - An open payment infrastructure

- A payment system built as an interoperable protocol that allows third-party vendors to build apps to provide payments as a service to all customers of participating banks.
- Open Payments connects you to multiple banks through one single unified API. Eliminates the complexity and frictions of many diverse integrations.
- Interoperability across banks: enables users to transfer funds to and from any bank account to anyone
  - Through the bank app (ICICI, SBI, HDFC, etc.) or any third-party app (Google Pay, PhonePe, Paytm).
  - Pre-UPI, a user would have to use the bank's native app (if available), say Yono, for SBI, and could initiate only a one-way transfer – from SBI $\rightarrow$ to other accounts in the same bank.
  - Now, using the same Yono app, the user can transfer funds across any bank, say from SBI to $\rightarrow$ HDFC.
  - The users are not locked within an app, unlike Venmo, Zelle, etc.
    - For instance, a Paytm user can receive and transfer funds to a PhonePe/Gpay user.

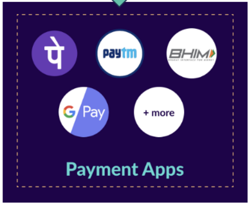
UPI and Credit

- Historically, India has been a high cash usage economy
  - A substantial portion of the workforce is engaged in the informal sector, relying on cash transactions.
  - Lack of credit/financial history $\implies$ Higher Information Asymmetry $\implies$ Low Credit Access
- Post-UPI – an exponential surge in digital payments usage
  - 35%-40% of adults now transact digitally $\implies$ enabling cash-flow-based lending to the traditionally underserved.
  - Since, UPI needs bank accounts, the newly created transaction history primarily lies with banks
  - Some fintechs offering payment services can also access this data conditional on consumer consent

UPI and Credit...

Cash Transactions - No financial history

Digitally verifiable Revenue



Cash-flow based lending

The Role of Open API in Banking

Customer owns the data and can share their data seamlessly across financial intermediaries

- Open Application programming interfaces (Open APIs) is a set of rules and tools that enable different financial intermediaries to seamlessly share customer data with each other securely and efficiently, with customer's explicit consent. `https://www.crif.digital/blog/the-role-of-api-in-open-banking/`.
- The benefits of Open API include
  - Customer consented data sharing across FIs (Banks→ Fintech, Fintech→Banks, Banks → Banks)
  - Efficient, secure and Automated
  - Any financial intermediaries with customer consent can access
- Open API is not only key to Open Banking, it is part of Open Banking ("Enabling open finance through APIs," BIS Representative Office for the Americas, 2020).

Landing Page

Research Question

India has a unique digital payment and data-sharing infrastructure : (a) generate real-time verifiable digital transactions data free; (b) customer can share data between any financial intermediaries

- How does digital payment infrastructure (India's UPI) combined with open data sharing affect credit markets?
    - Does it expand credit access?
    - If so, for whom?
        - Extensive margin: Ex-ante under-served or New to credit borrowers
        - Intensive margin: More credit to ex-ante included borrowers
- Which financial intermediaries facilitate credit access for the different sets of borrowers?
    - Traditional Banks vs. FinTechs lenders?
- Distributional impact: Does the distribution of borrowers change?

Our Contribution

- Impact on credit is theoretically ambiguous!
- Open payment infrastructure $\Longrightarrow$ breaks incumbent bank's information monopoly $\Longrightarrow$ lower relationship-specific investment $\Longrightarrow$ Lower credit supply from traditional banks
- Open banking-induced competition $\Longrightarrow$ Encourages innovation by new entrants (better screening technology) $\Longrightarrow$
- Our Primary Contribution:
  - The first large sample study to examine the impact of open digital payments infrastructure enabling cross-platform payments on credit markets $\Longrightarrow$ across institutions and across borrowers.
  - Examine the role of open API-enabled customer-driven data sharing on credit.
  - Using data on the universe of consumer loans from India.

Why India?- A Unique Setting- World Leader in DPI

- Globally, policies are still nascent regarding the structure and regulation of Open banking
- "India has become a leader in developing world-class digital public infrastructure (DPI)."–IMF Open Banking Worldwide
- India's publicly funded digital infrastructure (India stack) to spur open banking:
  - RBI and National National Payments Corporation of India (NPCI) under its Open Banking framework came out with payment system in 2016: Unified Payments Interface (UPI) and released its API for the banks and third-party.
  - UPI $\rightarrow$ Free interoperable payment systems-free for both financial intermediaries and consumers)- OUR FOCUS
- "Together, India's foundational DPI, has been harnessed to foster innovation and competition, expand markets, close gaps in financial inclusion"–IMF

Institutional Details- Unified Payment Interface (UPI)

Phenomenal Growth in UPI and Other Digital parameters

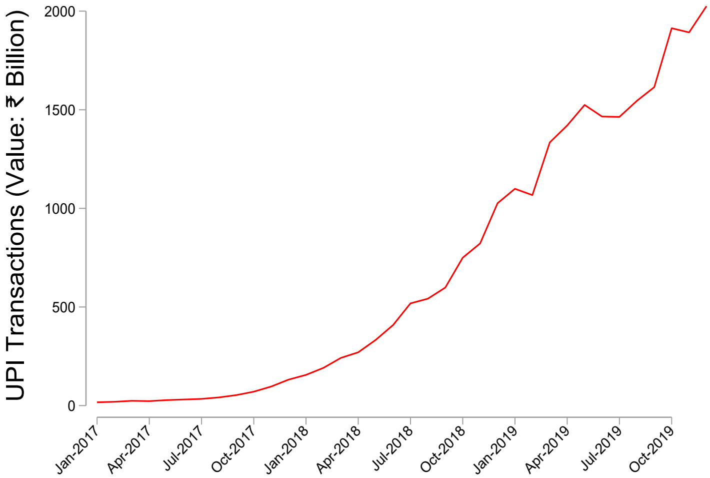
- More than 430 million unique UPI account [India's adult population is 952 million]
- UPI does average 10 billion transactions per month, amounting to USD 20.3 billion.
- More than 50% of all the payments and 75% of all retail digital transactions are on UPI
- Over 70 million merchants actively utilise UPI, using 256 million QR codes

- 1 billion smart phones in India, 738 million smart phone user
- As of 2023, the average Indian mobile user consumes 24.1 GB of data per month

- By July 2016, 99% of Indian households in both rural and urban India have at least one member with a bank account- Main driver is Pradhan Mantri Jan Dhan Yojana (JDY) started in 2014

India's Digital Revolution: The Perfect Storm

Phenomenal Growth in UPI



Major Data Collection Exercise: Proprietary data obtained from six different sources.

Data-1: Credit Data

- Detail Credit registry data on retail loans from Transunion CIBIL from October 2015-Jan 2019 at the pincode-month-year level for consumer loans $\Longrightarrow$ liability side data
    - Loan amount and number of accounts aggregated by pincode, by month across various categories
    - By lender type: Fintech and Banks
    - by borrower type: super-prime, prime plus, prime, near-prime, sub-prime, new-to-credit

Data-2: UPI data

- UPI volume data at the pincode-month from 2017 to 2019. Provided by one of the top 5 Payment service provider $\Longrightarrow$ cash-flow based variable generated from real time payment rail. Transaction side data

Data-3: Bank Branch Deposit Data

- Deposit data by bank type and bank branch, by pincode, by year from 2015 from RBI $\Longrightarrow$ used to construct the exposure measure used in the empirical strategy.

Data-4: JDY bank accounts data

- Number Jan Dhan Yojana (JDY) accounts opened, at the pincode-month level from Dept. of Financial Services, Govt. of India

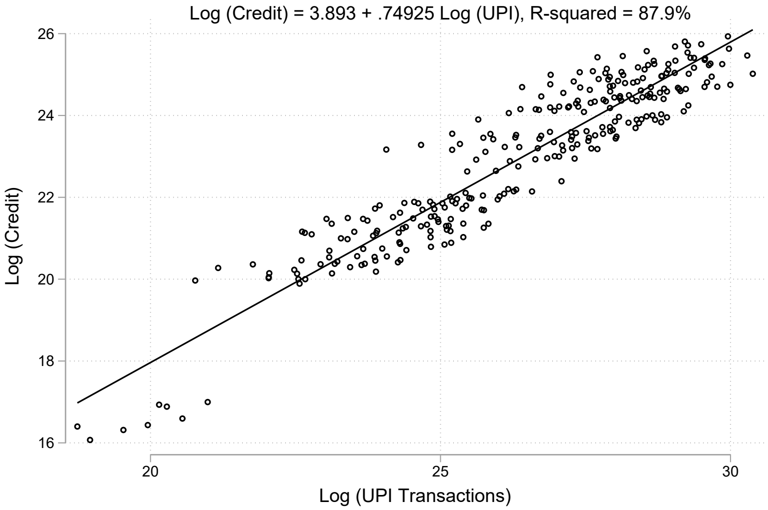
Data-5: Telecom Tower Data

- Location, provider name and date of setting up of 4G telecom towers from Telecom Regulatory Authority of India (TRAI)

Data-6: Data from one of the largest Fintech Firm

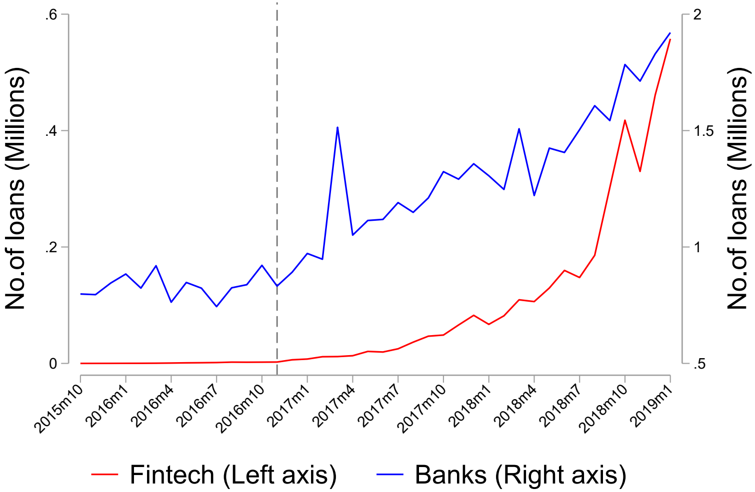
- Data from one of the largest Fintech lending firm in India: Data at Loan-level, borrower level information, information on UPI transaction of borrower, repeat borrower or not, detail credit bureaue data if available.

10% increase in UPI payments associated with 7% increase in credit



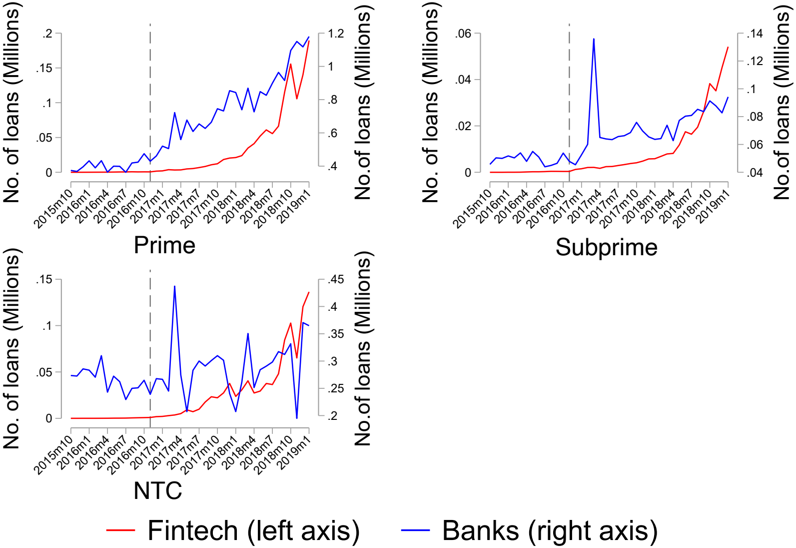
Observations at the state-month level for 2018 to 2020

Lender-wise trends



Credit growth across the board for all lenders post Nov-2016 (dashed grey vertical line) when UPI was introduced.

Trends by borrower type: prime, subprime, new-to-credit (NTC)



Credit growth across the board, though most stark for FinTech, especially for subprime and NTC

Identification and Empirical Strategy

Identification and Empirical Strategy

Exploit UPI adoption by banks

- A bank account is necessary to use the full functionality of UPI
- We exploit the early vs. late entry of different banks on the UPI platform (as classified by Govt. of India).
  - Banks live on UPI as of November 2016 available from GoI website (Dubey and Purnandam (2024)). `http://cashlessindia.gov.in/upi_services.html`.
- Exploit persistent differences in UPI take-up due to strong network externalities in the adoption of digital payments (Crouzet, Gupta, and Mezzanotti, 2023; Higgins, 2020).
- We compute the Exposure for pincode p as:

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

- We take the above and below the median of this exposure measure.

Balance Table | Summary Stats | Summary Stats (Pre) | Summary Stats (Post)

Identification and Empirical Strategy...

Grid-Time FEs

- Our bank-branch level deposit data allows us to measure exposure to early adopter banks at a granular pincode level using local deposit share of all early adopter banks.
- We compare treatment and control pincodes within narrow geographic grids.
    - We construct grids by dividing the Indian map into rectangular units of size 0.4×0.4 degrees.
    - A grid is bigger than a pincode, but smaller than a district.
    - Exploit pincode-level variation within these narrow neighborhoods (grids)
    - Control for time-varying local economic trends/shocks through Grid-time fixed effects.

Grid example | Balance Table | Summary Stats (Pre) | Summary Stats (Post)

Impact on Credit Access

Temporal Dynamics: Specification

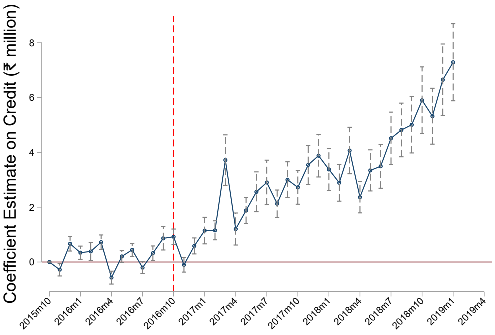
We use the following specification

$$\mathrm{Y}_{pd(p)t} = \alpha_{d(p)t} + \delta_{gt} + \theta_p + \beta_\tau \times \sum_{\substack{\tau=-10 \\ \tau\neq-1}}^{26} \mathbb{1}_\tau \times \text{High Exposure}_p + \epsilon_{pd(p)t} \tag{1}$$

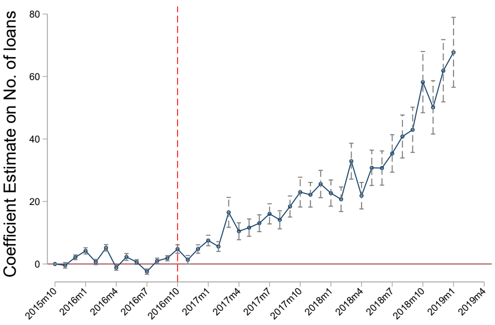
for pincode p belonging to district $d(p)$ in month-year t

- Observations are at the pincode-month-year level for Oct. 2015-Jan. 2019.
- $Y_{pd(p)t}$ is sanctioned amount (in INR million) or accounts.
- High Exposure is 1 for all observations that have above median UPI Exposure.
- $\alpha_{d(p)t}$, δ_{gt} and θ_p are the district-month-year, grid-month-year and pincode FE
- Standard errors are clustered at the pincode level.
- We use this specification for overall, FinTech and Bank credit.

Event Study: All loans

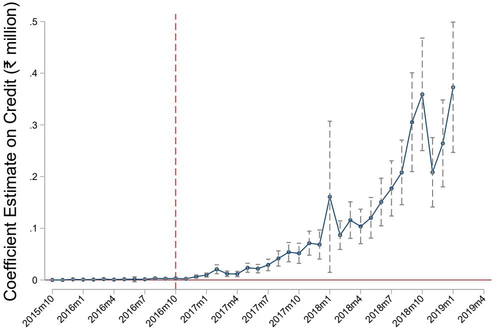


Amount



Accounts

Event Study: FinTech loans



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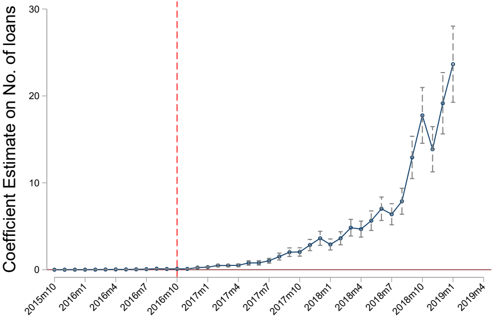
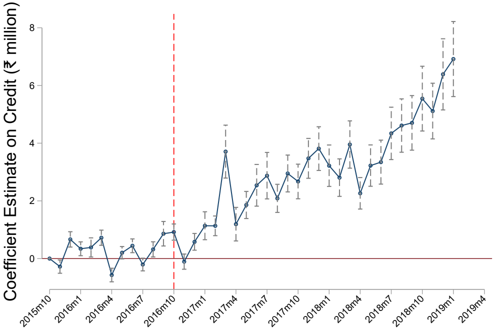
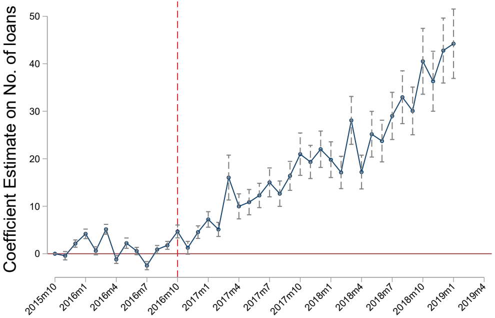


Accounts

Event Study: Bank loans



Amount



Accounts

UPI is a Game-changer: for Whom?

Increase in credit access across financial intermediaries

Increase relative to pre-period mean

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

Nearly 56x increase in the number of loans for FinTech lenders compared to a smaller (but substantial) 54% increase for banks attributable to a smaller base for FinTech lenders in the pre-period.

Empirical Specification

We estimate the impact on credit using the specification:

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

for pincode p belonging to district $d(p)$ in month-year t

- Observations are at the pincode-month-year level from Oct. 2015-Jan. 2019
- $Y_{pd(p)t}$ is sanctioned amount (in INR million) or accounts.
- $\alpha_{d(p)t}$, γ_{gt} and θ_p are the district-month-year, grid-month-year and pincode FE
- High UPI Exposure, takes value 1 for above-median UPI exposure, as of 2016 Q3. Post takes value 1 from November 2016 onward.
- Standard errors are clustered at the pincode level.
- We use this specification for overall credit and different subsamples across borrower types (subprime, new-to-credit, prime borrowers) and lender types (FinTech and Banks).

Impact on Credit

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

Standard errors in parentheses

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

Lenderwise Impact: All

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.112***	5.576***	4.133***	26.707***
	(0.018)	(0.974)	(0.420)	(2.988)
R^2	0.455	0.522	0.903	0.905
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	0.069	7.612	48.314
Post-UPI Mean	0.192	9.726	15.424	99.936
Dep. var mean	0.130	6.588	12.885	83.159
N	496640	496640	501040	501040

Standard errors in parentheses

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Nearly 56x increase in credit value (total effect), and a 81x increase in credit volume in high-exposure areas for FinTech lenders relative to the 54% and 55% respective increase for banks.

Lenderwise Impact: Subprime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.009***	0.518***	0.190***	1.074***
	(0.002)	(0.099)	(0.021)	(0.141)
R^2	0.530	0.526	0.811	0.822
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.013	0.436	2.873
Post-UPI Mean	0.015	0.939	0.874	5.440
Dep. var mean	0.010	0.638	0.732	4.606
N	496640	496640	501040	501040

Standard errors in parentheses

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

Nearly 23x increase in credit value, and a 40x increase in credit volume in high-exposure areas for fintech lenders relative to the 44% and 37% respective increase for banks.

Lenderwise Impact: New-to-credit

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.018***	1.415***	0.234***	2.812***
	(0.003)	(0.238)	(0.026)	(0.338)
R^2	0.579	0.554	0.860	0.906
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.017	1.907	15.028
Post-UPI Mean	0.036	2.647	2.464	21.395
Dep. var mean	0.024	1.792	2.283	19.326
N	496640	496640	501040	501040

Standard errors in parentheses

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

Nearly 45x increase in credit value, and a 83x increase in credit volume in high-exposure areas for fintech lenders, while bank loans increase by 12% and 19%, respectively.

Lenderwise Impact: Prime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.057***	1.945***	3.024***	18.677***
	(0.009)	(0.328)	(0.312)	(2.057)
R^2	0.299	0.518	0.883	0.887
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.023	4.187	23.742
Post-UPI Mean	0.095	3.304	9.712	58.443
Dep. var mean	0.064	2.238	7.917	47.165
N	496640	496640	501040	501040

Standard errors in parentheses

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

Nearly 57x increase in credit value, and a 85x increase in credit volume in high-exposure areas for fintech lenders, relative 72% and 79% respective increase for banks

Robustness

We conduct a battery of robustness tests, as follows

- Without Grid time FE: Analysis is repeated without grid-time FE. Results
- Neighborhood pairs: Instead of district-time fixed effects, we construct neighbourhood pair IDs, based on low exposure neighbours of high exposure pincodes, and control for pair-id x month-year FE Results
- Controlling for Demonetization: The baseline analysis compares pincodes within very narrow regions (grid-time FE) and hence estimates are not contaminated by the effects of the 2016 demonetization episode. Nonetheless, we control for variation in cash availability — using distance to the nearest currency chest as a proxy (Chodorow-Reich, 2018) — and find that the estimates are quantitatively and qualitatively very similar, suggesting that demonetization-related effects are not a concern in our empirical setting. Results

Mechanisms

$\nearrow$ UPI $\Longrightarrow$ $\nearrow$ lending

How does UPI enable this?

1. Launch of Open API by RBI enabled "Open Banking".
2. Jan Dhan Yojana (JDY) launched in 2014 made previously financially excluded borrowers come under financial inclusion.
   - By July 2016, 99% of Indian households have at least one member with a bank account-Main driver is JDY
3. Jio addressed the "digital divide"
   - Rapid geographic coverage of 4G networks
   - Jio also enabled UPI growth due to low cost of data
4. External validity test of digital verifiability of revenues: Directly link UPI transactions to credit access for small business borrowers (road-side kiosks) using data from one of the largest FinTech lender

Mechanism 1: Expansion through Open API

Exploit staggered onboarding of RBI API

- Customer owns the data and can share their data seamlessly across financial intermediaries
- Open banking was facilitated by the RBI Open API
- We exploit the staggered onboarding of banks onto the RBI API
- We compute the Exposure for pincode p in month m as:

$$\text{API Exposure}_{pm} = \frac{\text{Total deposits of API onboarded banks}_{pm}}{\text{Total Deposit of all Banks}_{p}}$$

Empirical Specification

We estimate the differential impact of staggered open API adoption on credit using the specification with grid-FE, as before:

$$Y_{pd(p)t} = \alpha_{d(p)t} + \delta_{gt} + \theta_p + \gamma \times \text{API Exposure}_{pm} \times \text{High UPI Exposure}_p$$
$$+\beta_1 \times \text{High UPI Exposure}_p \times \text{Post} + \beta_2 \times \text{API Exposure}_{pm} + \epsilon_{pd(p)t}$$

for pincode p belonging to district $d(p)$ in month-year t

- Observations are at the pincode-month-year level from October 2015 to January 2019
- $Y_{pd(p)t}$ is sanctioned amount (in INR million) or accounts.
- High UPI Exposure takes value 1 for pincodes with above median UPI Exposure
- $\alpha_{d(p)t}$,δ_{gt} and θ_p refer to the district-month-year, grid-month-year and pincode fixed effects
- Standard errors are clustered at the pincode level.

Impact on Credit

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

Standard errors in parentheses

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

Lenderwise Impact: All

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
API Exposure × High UPI Exposure	0.231***	12.686***	3.454***	26.276***
	(0.036)	(1.965)	(0.409)	(2.971)
High UPI Exposure$_p$	0.049***	2.123***	1.918***	11.609***
	(0.012)	(0.530)	(0.243)	(1.719)
API Exposure$_{mp}$	-0.017	-0.703	-0.059	-3.633
	(0.021)	(1.032)	(0.291)	(2.233)
R^2	0.467	0.538	0.947	0.946
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	0.069	9.744	61.747
Post-UPI Mean	0.192	9.726	15.424	99.936
Dep. var mean	0.127	6.444	13.533	86.851
N	459392	459392	463462	463462

Standard errors in parentheses

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

Lenderwise Impact: Subprime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
API Exposure$_{mp}$× High UPI Exposure$_p$	0.015***	1.169***	0.110***	0.809***
	(0.002)	(0.196)	(0.022)	(0.113)
High UPI Exposure$_p$	0.004***	0.198***	0.090***	0.398***
	(0.001)	(0.054)	(0.013)	(0.088)
API Exposure$_{mp}$	0.000	-0.021	0.026	-0.054
	(0.002)	(0.103)	(0.022)	(0.092)
R^2	0.548	0.541	0.847	0.846
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.013	0.563	3.684
Post-UPI Mean	0.015	0.939	0.874	5.440
Dep. var mean	0.010	0.623	0.776	4.854
N	459392	459392	463462	463462

Standard errors in parentheses

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

Lenderwise Impact: NTC

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
API Exposure$_{mp}\times$ High UPI Exposure$_p$	0.040***	2.705***	0.046	1.236***
	(0.006)	(0.411)	(0.030)	(0.269)
High UPI Exposure$_p$	0.008***	0.679***	-0.071***	0.120
	(0.002)	(0.149)	(0.020)	(0.179)
API Exposure$_{mp}$	-0.001	-0.194	-0.010	-0.075
	(0.003)	(0.237)	(0.023)	(0.213)
R^2	0.595	0.570	0.903	0.948
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.017	2.511	19.629
Post-UPI Mean	0.036	2.647	2.464	21.395
Dep. var mean	0.024	1.757	2.486	20.723
N	459392	459392	463462	463462

Standard errors in parentheses

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

Lenderwise Impact: Prime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
API Exposure$_{mp}\times$ High UPI Exposure$_p$	0.117***	4.763***	2.777***	20.234***
	(0.021)	(0.712)	(0.339)	(2.305)
High UPI Exposure$_p$	0.025***	0.650***	1.539***	9.120***
	(0.007)	(0.172)	(0.192)	(1.244)
API Exposure$_{mp}$	-0.015	-0.304	-0.099	-3.029*
	(0.012)	(0.376)	(0.237)	(1.734)
R^2	0.306	0.533	0.926	0.928
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.023	5.299	29.992
Post-UPI Mean	0.095	3.304	9.712	58.443
Dep. var mean	0.063	2.186	8.231	48.738
N	459392	459392	463462	463462

Standard errors in parentheses

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

Mechanism 2: JDY bank account holders- Financial formalization

Empirical Specification - Difference-in-differences-in-differences

We estimate the differential impact of financial formalization on credit using the specification with grid-FE, as before:

$$Y_{pd(p)t} = \alpha_{d(p)t} + \delta_{gt} + \theta_p + \gamma \times \text{UPI Exposure}_p \times \text{High JDY}_p \times \text{Post} + \beta \times \text{UPI Exposure}_p \times \text{Post} + \beta_2 \times \text{High JDY} \times \text{Post} + \epsilon_{pd(p)t}$$

for pincode p belonging to district $d(p)$ in month-year t

- Observations are at the pincode-month-year level from October 2015-January 2019
- $Y_{pd(p)t}$ is sanctioned amount (in INR million) or accounts.
- High JDY_p takes value 1 for pincodes, with above-first tercile cumulative number of JDY bank accounts, as of November 2016.
- High Exposure, takes value 1 for above-median UPI exposure, as of 2016 Q3. Post takes value 1 from 2016 November onwards.
- $\alpha_{d(p)t}$,δ_{gt} and θ_p refer to the district-month-year, grid-month-year and pincode fixed effects

Mechanism: Financial Formalization

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

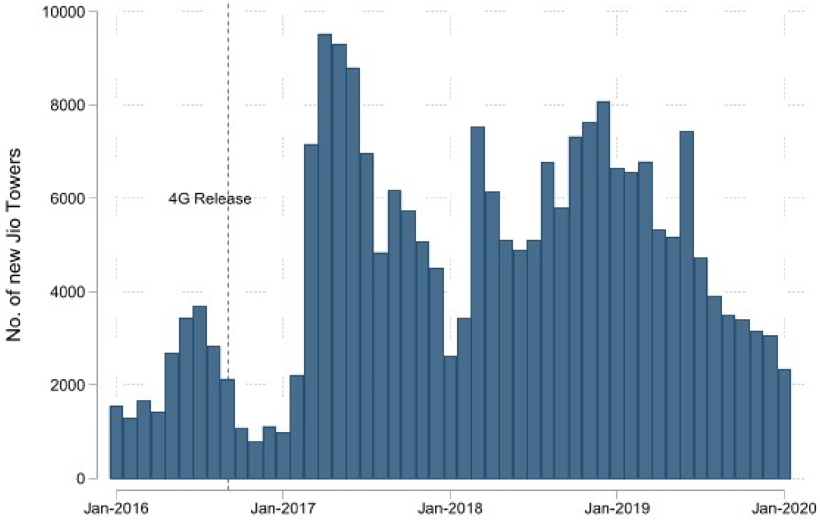
Standard errors in parentheses

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

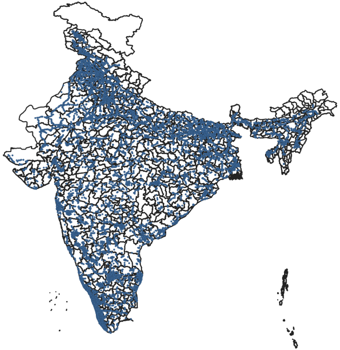
Subsample: High JDY Subsample: Low JDY

Mechanism 3: Cost of Internet: 4G connectivity through Jio

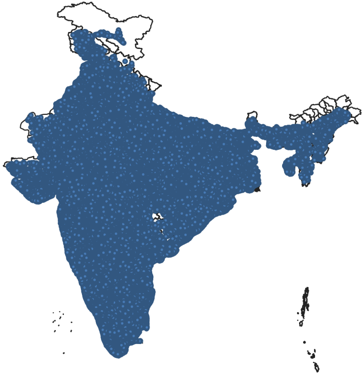
Rapid rollout of 4G Jio Towers starting September 2016



. . . and brought previously excluded areas under 4G



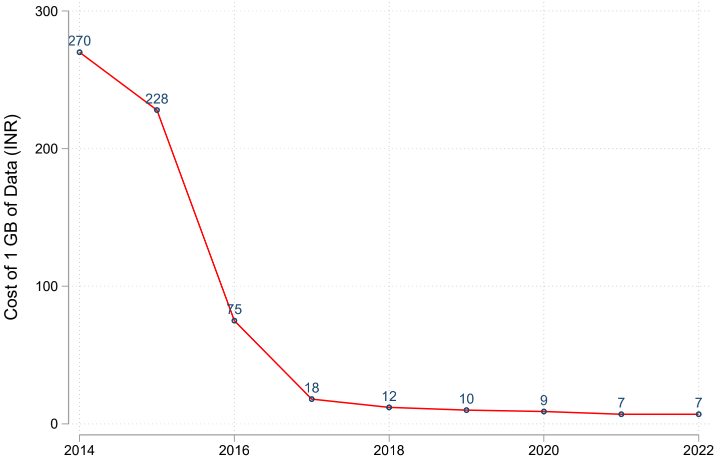
2016



2020

→ The average distance to a tower decreased from 15.1 km in 2016 to 2.1 km in 2020

. . . that lowered data costs exponentially



Source: Nandan Nilekani, Blume Research, NPCI Statistics

Empirical Specification

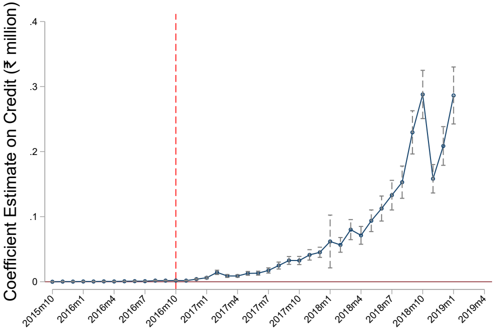
We estimate the differential impact of early 4G adoption on credit using the specification with grid-FE, as before:

$$Y_{pd(p)t} = \alpha_{d(p)t} + \delta_{gt} + \theta_p + \gamma \times \text{High UPI Exposure}_p \times \text{Early Jio}_p \times \text{Post} + \beta \times \text{High UPI Exposure}_p \times \text{Post} + \beta_2 \times \text{Early Jio} \times \text{Post} + \epsilon_{pd(p)t}$$

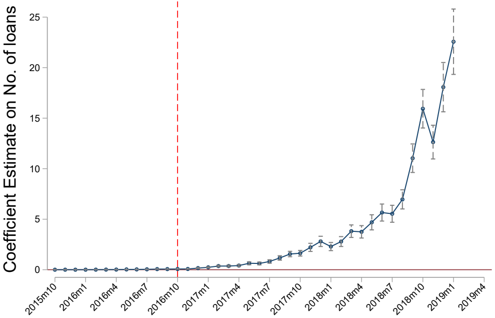
for pincode p belonging to district $d(p)$ in month-year t

- Observations are at the pincode-month-year level from October 2015 to January 2019
- $Y_{pd(p)t}$ is sanctioned amount (in INR million) or accounts.
- Early Jio identifies pincodes that received a Jio tower within 6 km by 2017 Q1.
- $\alpha_{d(p)t}$,δ_{gt} and θ_p refer to the district-month-year, grid-month-year and pincode fixed effects
- High Exposure, takes value 1 for above-median UPI exposure, as of 2016 Q3. Post takes value 1 from 2016 November onwards.
- Standard errors are clustered at the pincode level.
- Some checks
  - JIO UPI correlation
  - Balance Table Jio
  - Jio Entry R-square

Event Study: FinTech loans

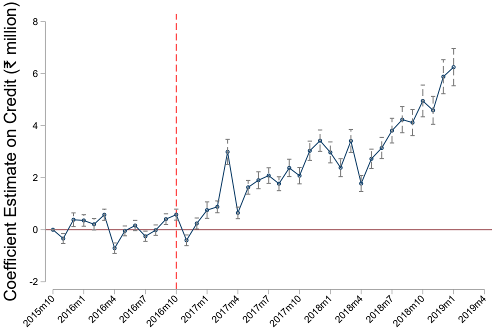


Amount

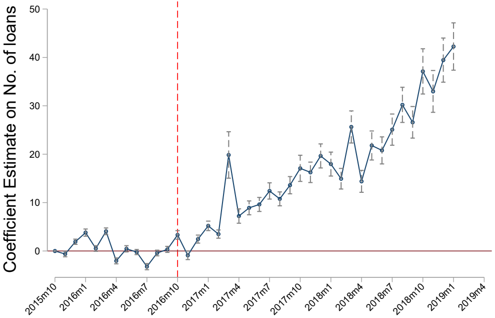


Accounts

Event Study: Bank loans



Amount



Accounts

Motivation: Subsample regressions with non-jio pincodes

- One may be concerned that pincodes with early and late access to 4G may experience other contemporaneous economic shocks.
- Our event study figures and balance tests help address these concerns to a large extent.
- Nonetheless, we restrict our sample to pincodes with early access to a non-Jio tower, that is we hold access to 4g constant, For robustness we repeat these tests with all pincodes.
    - Non-jio operators comprise other major mobile telephony providers in India.

Impact on FinTech Credit

	(1)	(2)	(3)	(4)
Lender	All		NTC	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
$\text{Early}_{\text{Jio}}$ × High UPI Exposure × Post	0.185***	6.082**	0.025***	1.152*
	(0.056)	(2.631)	(0.009)	(0.674)
High Exposure × Post	0.076*	5.339***	0.014**	1.575***
	(0.040)	(1.997)	(0.007)	(0.524)
$\text{Early}_{\text{Jio}}$ × Post	0.042	4.235**	0.013**	1.323**
	(0.041)	(2.145)	(0.006)	(0.536)
R^2	0.459	0.541	0.595	0.572
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	0.069	0.000	0.017
Post-UPI Mean	0.452	21.059	0.078	5.329
Dep. var mean	0.127	6.444	0.024	1.757
N	186520	186520	186520	186520

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

All Pincodes | Subsample: Early Jio | Subsample: Late Jio

Impact on Bank Credit

	(1)	(2)	(3)	(4)
Lender	All		NTC	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
$\text{Early}_{\text{Jio}} \times$ High UPI Exposure $\times$ Post	4.288***	33.928***	-0.108	1.866**
	(1.100)	(8.344)	(0.087)	(0.810)
High Exposure $\times$ Post	1.795**	8.229	-0.042	-0.843
	(0.802)	(6.155)	(0.081)	(0.640)
$\text{Early}_{\text{Jio}} \times$ Post	1.443*	10.993*	-0.034	0.107
	(0.793)	(5.981)	(0.080)	(0.585)
R^2	0.944	0.944	0.907	0.953
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	9.744	61.747	2.511	19.629
Post-UPI Mean	30.926	213.721	4.255	42.568
Dep. var mean	13.533	86.851	2.486	20.723
N	187680	187680	187680	187680

Standard errors in parentheses

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

All Pincodes | Subsample: Early Jio | Subsample: Late Jio

One of the Largest FinTech Lender:

Digital Verifiability of Revenue

Data Description

We obtain loan-level data from one of the largest FinTech lenders in India:

- Application Data for the years 2020-2023, which includes
  - Loan Size
  - Loan Duration
  - Internal Credit Score (DRS Score)
  - Merchant Category [concentrate on street vendors]
- Monthly Transactions Data that includes UPI transactions count and value
- Pin code level aggregate bank UPI exposure in the year 2015

Empirical Specifications

We estimate the impact of QR-based UPI Transactions count/value on loan-level variables using the following two specification

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

for a merchant i belonging to a pincode $p(i)$ and state $s(i)$ in month t

- Y_{it} takes the following values: Internal credit score, sanctioned loan amount, and interest rate for loans taken by road-side kiosks.
- X takes the following values: QR-UPI Transaction count$_{it}$ and Log of QR-UPI Transaction Values$_{it}$.
- $\alpha_{s(i)t}$ refer to the state-time fixed effects.
- Standard errors are clustered at the pincode level

Digital Verifiability

All Loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable	Loan Size (in 000's)		Interest Rate (in %)		Internal Credit Score			
					Score		Dummy	
Log(QR T.Value)	34.695***		-0.019***		1.533***		0.009***	
	(0.871)		(0.001)		(0.033)		(0.001)	
Log(QR T.Count)		27.904***		-0.015***		1.314***		0.010***
		(0.689)		(0.001)		(0.031)		(0.001)
R^2	0.166	0.140	0.132	0.131	0.239	0.224	0.938	0.938
State Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Dep Var Mean	109.516	109.516	1.953	1.953	15.055	15.055	0.434	0.434
N	39602	39602	43745	43745	18973	18973	43745	43745

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

- Digital verifiability: QR-based UPI Transactions positively correlate with loan size and internal credit score and negatively correlate with interest rate.

Impact on Default

Comparing pre and post

Default rates denote the number of loans that defaulted within one year of origination in a pincode.

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

Default: Empirical Specification

We estimate the impact on default using the specification:

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

for pincode p belonging to district $d(p)$ in month-year t

- Observations are at the pincode-month-year level from October 2015 to january 2019
- $Y_{pd(p)t}$ is the account based default rate
- $\alpha_{d(p)t}$, δ_{gt} and θ_p refer to the district-month-year, grid-month-year and pincode fixed effects
- Standard errors are clustered at the pincode level.
- We use this specification for overall credit and different subsamples across borrower types (subprime, new-to-credit, prime borrowers) and lender types (FinTech and Banks).

Impact on Default: FinTech

	(1)	(2)	(3)	(4)
Dependent variable	Default Rate			
	All	NTC	Subprime	Prime
High UPI Exposure$_p \times$ Post	-0.004	-0.039**	-0.006	0.003
	(0.011)	(0.019)	(0.033)	(0.012)
R^2	0.359	0.406	0.417	0.385
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.066	0.055	0.129	0.026
Post-UPI Mean	0.073	0.086	0.105	0.048
Dep. var mean	0.072	0.086	0.106	0.048
N	157725	103332	51493	98308

Standard errors in parentheses

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

Impact on Default: Banks

	(1)	(2)	(3)	(4)
Dependent variable	Default Rate			
	All	NTC	Subprime	Prime
High UPI Exposure$_p \times$ Post	0.000	0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.002)	(0.000)
R^2	0.295	0.246	0.318	0.265
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.018	0.018	0.048	0.012
Post-UPI Mean	0.032	0.033	0.066	0.026
Dep. var mean	0.028	0.029	0.062	0.022
N	460013	432438	283891	446827

Standard errors in parentheses

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

Conclusion

- 850 million individuals in India are credit unserved/under-served.
  - A global phenomena!
  - First-order question: How do we expand access to the marginal population?
  - Our Focus: Can digital public infrastructure enable credit access?
- Using the universe of credit bureau data in India, we find
  - Digital payment infrastructure (UPI) helps boost access to credit for the underserved.
  - Open API significantly boosts this effect, led by fintechs.
  - Our results suggest that fintechs leverage these open APIs enabled access to customer's payments data to expand access to credit to subprime and New-to-credit.
- Financial Inclusion 2.0: Fintech expands credit in regions with more of JDY account holders (previously excluded borrowers!)
- Digital Inclusion and Internet Connectivity: Effects are stronger in regions with cheap and better internet connectivity.

Thank You!

Appendix

Comparing Pre- and post- November 2016

High exposure areas see greater increases in credit access.

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

Main

Summary Statistics

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

Main

Summary statistics (Pre)

	Mean	Median	St. Dev
Total Loan Amount (Million INR)	9.75	2.59	29.28
Total no. of loans	61.82	15.00	187.97
Subprime Loan Amount (Million INR)	0.56	0.05	1.80
Subprime no. of loans	3.70	1.00	11.46
New-to-credit Loan Amount (Million INR)	2.51	0.87	6.15
New-to-credit no. of loans	19.65	6.00	55.12
FinTech Loan Amount (Million INR)	0.00	0.00	0.05
FinTech no. of loans	0.07	0.00	0.65
Banks Loan Amount (Million INR)	9.74	2.59	29.27
Banks no, of loans	61.75	15.00	187.62

Main

Summary statistics (Post)

	Mean	Median	St. Dev
Total Loan Amount (Million INR)	15.54	4.26	47.45
Total no. of loans	108.45	24.00	359.68
Subprime Loan Amount (Million INR)	0.89	0.15	2.77
Subprime no. of loans	6.33	1.00	25.96
New-to-credit Loan Amount (Million INR)	2.51	0.93	6.11
New-to-credit no. of loans	23.84	7.00	71.29
FinTech Loan Amount (Million INR)	0.19	0.00	1.48
FinTech no. of loans	9.51	0.00	61.41
Banks Loan Amount (Million INR)	15.36	4.23	46.52
Banks no, of loans	98.94	22.00	317.36
UPI Transactions (Value: Million INR)	8.93	2.13	21.13
UPI Transactions (Volume: 1000s)	3.89	1.07	8.46

Main

Balance Table

High vs Low Exposure areas

No significant difference across high and low exposure areas in credit growth or economic activity (nightlights) in the pre-period.

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

Main

Balance Table (Jio)

JIO entered areas with lower credit and nightlight growth earlier. Admittedly JIO's entry decision is not completely random. However, the fact that JIO entered areas with lower credit growth first would bias the estimates against finding a significant effect.

	(1) Early Jio		(2) Late Jio		(1)-(2) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Total Credit per capita	7301	1081.652 (97.212)	5190	238.632 (22.758)	12491	843.020***
Total Credit per capita (Growth)	7301	0.127 (0.003)	5187	0.193 (0.004)	12488	-0.066***
Subprime + NTC Loan Share per capita	7301	0.000 (0.000)	5188	0.000 (0.000)	12489	-0.000
Subprime + NTC Loan Share per capita (Growth)	7297	0.087 (0.003)	5182	0.121 (0.005)	12479	-0.034***
Nightlight Intensity per capita	7301	0.001 (0.000)	5190	0.000 (0.000)	12491	0.001***
Nightlight per capita (Growth)	7298	0.052 (0.002)	5182	0.109 (0.016)	12480	-0.056***

Main

R-square-Results of Jio Entry

Higher credit growth areas were covered by JIO later than low credit growth areas. Importantly, for us, credit and economic activity taken together (column 8) only explain 3.3% of the variation in JIO entry decision.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable					Jio entry			
Growth of Total Credit per capita	0.510^{***}							0.366^{***}
	(0.082)							(0.083)
Growth of Subprime + NTC Credit per capita		0.461^{***}						0.357^{***}
		(0.067)						(0.066)
Growth of Nightlights per capita			0.001					-0.016
			(0.033)					(0.026)
Total Credit per capita				0.000				-0.000^{*}
				(0.000)				(0.000)
Subprime + NTC Credit per capita					3351.685^{*}			10037.054^{***}
					(1972.737)			(3625.300)
Nightlights per capita						26.393^{**}		-38.221
						(11.612)		(42.835)
High Exposure							-0.030	-0.016
							(0.044)	(0.042)
Constant	1.858^{***}	1.891^{***}	1.935^{***}	1.936^{***}	1.900^{***}	1.920^{***}	1.951^{***}	1.799^{***}
	(0.038)	(0.035)	(0.034)	(0.034)	(0.039)	(0.035)	(0.041)	(0.046)
R^2	0.005	0.006	0.000	0.000	0.010	0.005	0.000	0.033
N	11884	11878	11885	11886	11886	11886	11886	11877

Standard errors in parentheses
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Main

UPI -Jio Correlation

Pincodes that were early to receive JIO tower also exhibit higher UPI adoption.

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

Standard errors in parentheses

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

Main

Impact on FinTech Credit (All Pincodes)

	(1)	(2)	(3)	(4)
Lender	All		NTC	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
$\text{Early}_{\text{Jio}} \times$ High UPI Exposure $\times$ Post	0.135***	6.071***	0.021***	1.488***
	(0.024)	(1.234)	(0.004)	(0.307)
High Exposure $\times$ Post	0.026***	1.684***	0.005***	0.456***
	(0.008)	(0.430)	(0.001)	(0.117)
$\text{Early}_{\text{Jio}} \times$ Post	0.007	1.325**	0.004**	0.438***
	(0.011)	(0.576)	(0.002)	(0.146)
R^2	0.455	0.523	0.579	0.554
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	0.069	0.000	0.017
Post-UPI Mean	0.192	9.726	0.036	2.647
Dep. var mean	0.127	6.444	0.024	1.757
N	496640	496640	496640	496640

Standard errors in parentheses

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

Main

Impact on Bank Credit (All Pincodes)

	(1)	(2)	(3)	(4)
Lender	All		NTC	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
$\text{Early}_{\text{Jio}}$ × High UPI Exposure × Post	3.144***	21.710***	-0.069**	0.711**
	(0.449)	(3.305)	(0.031)	(0.300)
High Exposure × Post	0.891***	5.093***	-0.029	-0.076
	(0.184)	(1.312)	(0.019)	(0.139)
$\text{Early}_{\text{Jio}}$ × Post	0.752***	4.746***	-0.039**	0.001
	(0.223)	(1.656)	(0.019)	(0.170)
R^2	0.944	0.943	0.907	0.949
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Pre-UPI Mean	9.744	61.747	2.511	19.629
Post-UPI Mean	15.424	99.936	2.464	21.395
Dep. var mean	13.533	86.851	2.486	20.723
N	501040	501040	501040	501040

Standard errors in parentheses

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

Main

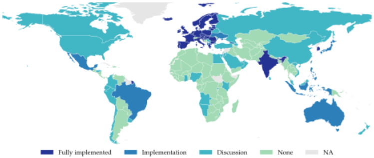
Open Banking: Worldwide Adoption

Babina et al. 2023

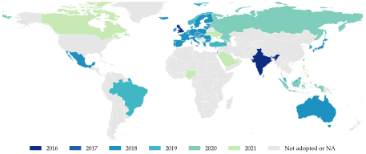
Main

Figure 1: Government-led Open Banking Regimes Around the World

Note: These maps show the current implementation status of government-led open banking policies and the year in which the major open banking policy was passed. Panel (a) shows the implementation status of their government open banking policies. Fully implemented corresponds to countries that have implemented open banking government policies; Implementation to those that have determined the specifics of the open banking approach and are currently implementing it; Discussion to those either considering implementing open banking policies or discussing that implementation; None to those with no government open banking approach; and NA to those where we have not collected data. Panel (b) shows the passage year of countries' major open banking policies. Data on government open banking policies is current as of October 2021.

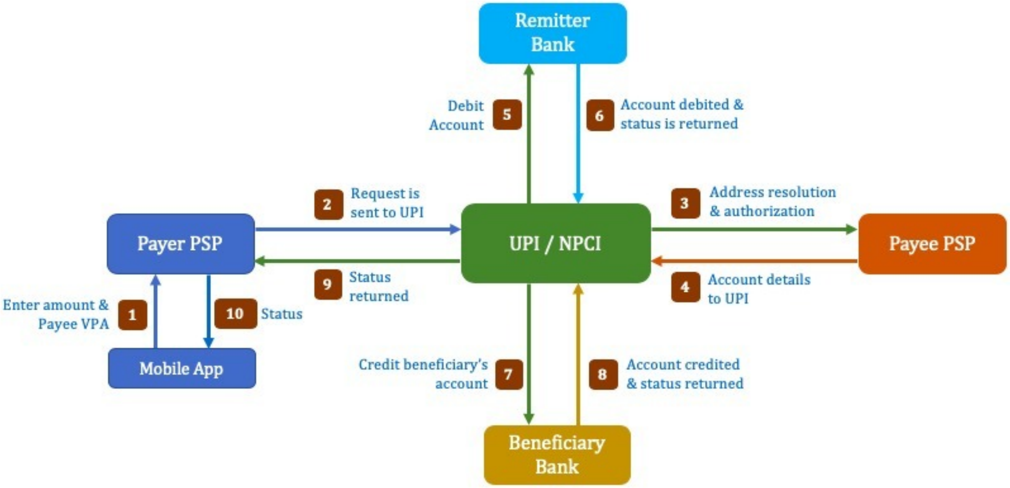


(a) Government open banking policy implementation status



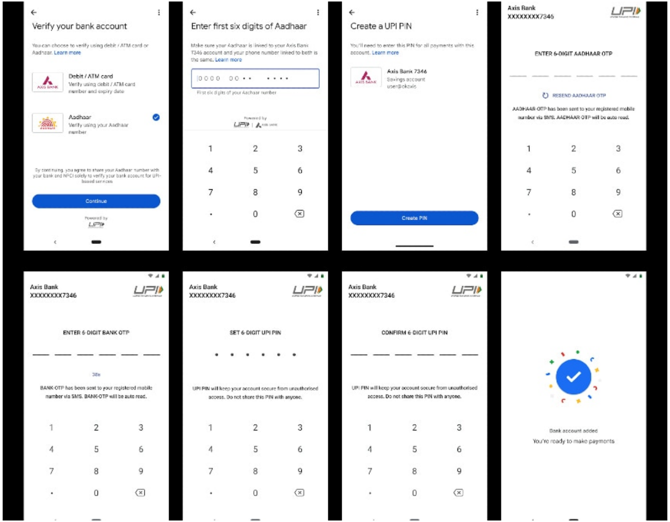
(b) Timeline of open banking adoption

UPI-Payments Flow Chart



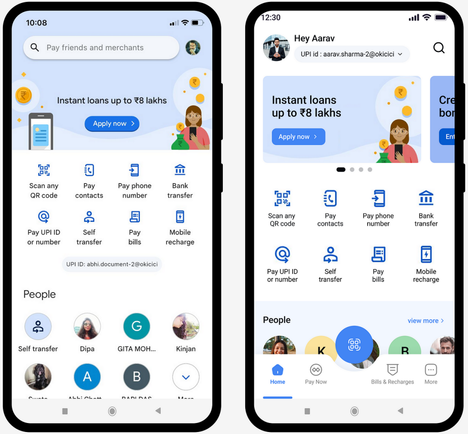
Main

UPI Account Open



Main

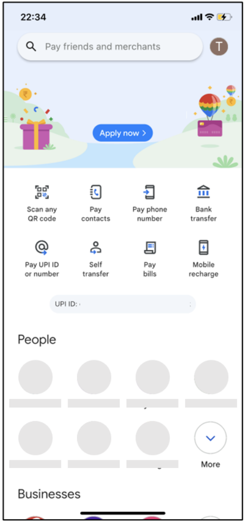
Landing Page-TPP

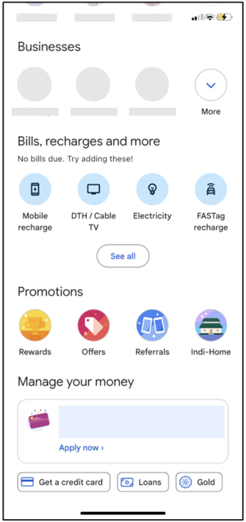


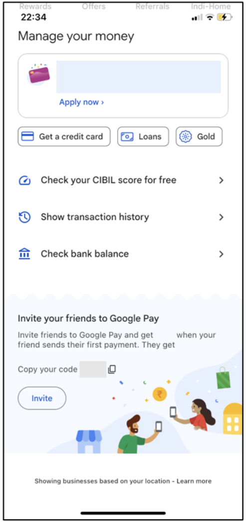
Old Design **New Design**

Main

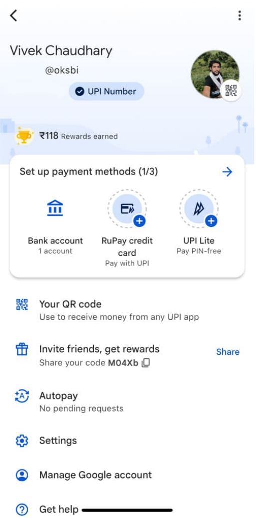
Google Pay Interface

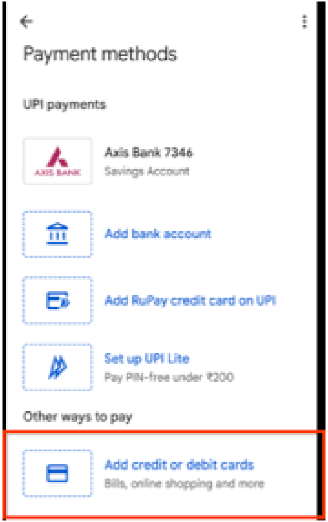


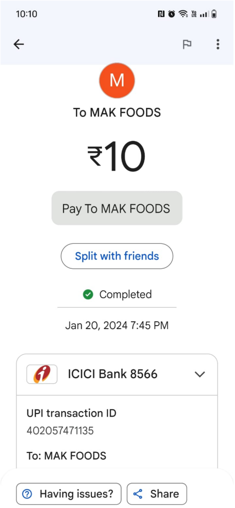




Payment Method

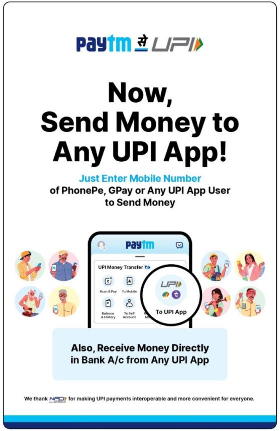






Main

Interoperability



Main

Why Prime Increasing

- On average, loan size in prime is small. 6 million INR loan given in a pincode-month to 100 accounts. So, on an average each account in prime sector gets about Rs 60,000. This is small ticket
- Existing literature have shown that Fintech loan for prime segment also increases due to better convenience and speed offered by Fintech (Buchak et al. 2018)
- Loan to prime borrowers through the UPI handle. For example, Gpay is UPI handle. Gpay has partnered with many banks and other lenders in India to advertise loans to individuals and merchants on the Gpay app. Gpay is enabling credit
    - average such loans in Gpay is under USD 360 in size and 80% of all these loans have been credited to Indians living in smaller cities and towns. (source: Techcrunch report, Oct 19,2023)

Main

High JDY: Subsample DiD

	(1)	(2)	(3)	(4)	(5)	(6)
Lender	All		FinTech		NTC + FinTech	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	3.885***	31.411***	-0.022	2.399***	0.022***	1.662***
	(0.504)	(4.594)	(0.037)	(0.518)	(0.004)	(0.314)
R^2	0.947	0.923	0.916	0.947	0.630	0.622
Pincode FE	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	14.069	90.476	3.517	28.337	0.001	0.027
Post-UPI Mean	22.426	158.634	3.496	34.163	0.051	3.731
Dep. var mean	19.710	136.483	3.503	32.269	0.035	2.527
N	290400	290400	290400	290400	288640	288640

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

Main

Low JDY: Subsample DiD

	(1)	(2)	(3)	(4)	(5)	(6)
Lender	All		FinTech		NTC + FinTech	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.402**	2.365	-0.038***	-0.049	0.003	0.209*
	(0.162)	(1.601)	(0.014)	(0.231)	(0.002)	(0.121)
R^2	0.894	0.906	0.884	0.894	0.558	0.656
Pincode FE	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	3.745	23.446	1.029	7.758	0.000	0.006
Post-UPI Mean	6.029	42.054	1.044	9.856	0.014	1.126
Dep. var mean	5.287	36.006	1.039	9.174	0.010	0.762
N	187160	187160	187160	187160	184760	184760

Standard errors in parentheses
$^{*}\ p < 0.1,\ ^{**}\ p < 0.05,\ ^{***}\ p < 0.01$

Main

Effect on Credit (Early Jio Subsample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lender	FinTech				Banks			
Sample	All		New-to-credit		All		New-to-credit	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act	Amt (Million INR)	Act	Amt (Million INR)	Act
High Exposure × Post	0.337***	13.546***	0.046***	3.087***	6.404***	46.072***	-0.089	1.859***
	(0.064)	(2.984)	(0.010)	(0.732)	(1.059)	(8.016)	(0.069)	(0.687)
R^2	0.501	0.584	0.645	0.622	0.959	0.959	0.893	0.949
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.069	0.000	0.017	9.744	61.747	2.511	19.629
Post-UPI Mean	0.384	18.353	0.068	4.738	26.826	182.273	3.773	36.625
Dep. var mean	0.127	6.444	0.024	1.757	13.533	86.851	2.486	20.723
N	163100	163100	163100	164173	164173	164173	164173	

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

Main

Effect of FinTech Credit (Late Jio Subsample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lender	FinTech				Banks			
Sample	All		New-to-credit		All		New-to-credit	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act	Amt (Million INR)	Act	Amt (Million INR)	Act
High Exposure × Post	0.048*	5.438**	0.015**	2.206**	2.079**	12.453**	0.273*	1.142
	(0.026)	(2.488)	(0.007)	(0.880)	(1.000)	(6.085)	(0.154)	(1.255)
R^2	0.724	0.759	0.636	0.754	0.945	0.957	0.893	0.921
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.069	0.000	0.017	9.744	61.747	2.511	19.629
Post-UPI Mean	0.057	4.544	0.016	1.575	6.268	34.409	1.333	8.906
Dep. var mean	0.127	6.444	0.024	1.757	13.533	86.851	2.486	20.723
N	61463	61463	61463	61463	61830	61830	61830	61830

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

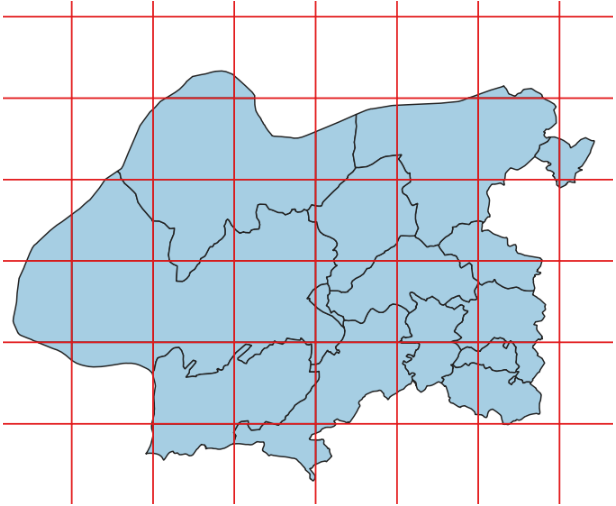
Main

Constructing Grids

- To control for granular geographical effects, we construct grids by dividing the Indian map into rectangular units of size 0.4×0.4 degrees.
    - A grid is bigger than a pincode, but smaller than a district.
- As pincodes can belong to multiple grids, we assign them to the grid where it contributes the maximum area.
- We include grid-time fixed effects to control for time-varying local economic shocks and trends.
    - Treatment effects identified through within-grid-time variation across high- and low-exposure pincodes.

Main

Example: Jaisalmer, Rajasthan



Main

Results without Grid FE

Impact on Credit

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

Standard errors in parentheses

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

Main

Lenderwise Impact: All

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.105***	5.237***	2.911***	19.112***
	(0.011)	(0.484)	(0.237)	(1.692)
R^2	0.426	0.476	0.939	0.936
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.070	9.743	61.827
Post-UPI Mean	0.190	9.622	15.356	99.066
Dep. var mean	0.129	6.518	13.532	86.964
N	504280	504280	508840	508840

Standard errors in parentheses

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

Main

Lenderwise Impact: Subprime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.008***	0.481***	0.119***	0.621***
	(0.001)	(0.048)	(0.012)	(0.069)
R^2	0.504	0.485	0.828	0.789
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.013	0.563	3.689
Post-UPI Mean	0.015	0.928	0.877	5.414
Dep. var mean	0.010	0.630	0.775	4.853
N	504280	504280	508840	508840

Standard errors in parentheses

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

Lenderwise Impact: NTC

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.017***	1.331***	-0.080***	0.269*
	(0.002)	(0.124)	(0.018)	(0.153)
R^2	0.544	0.512	0.901	0.945
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.018	2.506	19.642
Post-UPI Mean	0.035	2.623	2.468	21.263
Dep. var mean	0.024	1.777	2.480	20.736
N	504280	504280	508840	508840

Standard errors in parentheses

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

Main

Lenderwise Impact: Prime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.054***	1.846***	2.366***	15.132***
	(0.006)	(0.172)	(0.192)	(1.301)
R^2	0.272	0.472	0.914	0.912
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.023	5.303	30.039
Post-UPI Mean	0.094	3.265	9.648	57.861
Dep. var mean	0.063	2.211	8.236	48.819
N	504280	504280	508840	508840

Standard errors in parentheses

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

Main

Robustness: Controlling for demonetisation

Impact on Credit: Controlling for demonetisation

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

Standard errors in parentheses

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

Main

Robustness: Comparing Neighbouring Pincodes
Alternative specification

Impact on Credit: Neighbourhood pair FE

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

Standard errors in parentheses

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

Main

Lenderwise Impact: All

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure $\times$ Post	0.141***	6.199***	4.101***	26.721***
	(0.023)	(0.752)	(0.419)	(3.205)
R^2	0.662	0.748	0.974	0.971
Pincode FE	Y	Y	Y	Y
Neighbourhood-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.004	0.095	12.476	81.078
Post-UPI Mean	0.257	12.458	19.624	129.866
Dep. var mean	0.174	8.440	17.301	114.010
N	428000	428000	428000	428000

Standard errors in parentheses

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

Main

Lenderwise Impact: Subprime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.009***	0.585***	0.192***	0.879***
	(0.002)	(0.075)	(0.021)	(0.143)
R^2	0.756	0.750	0.935	0.947
Pincode FE	Y	Y	Y	Y
Neighbourhood-time- FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.018	0.684	4.764
Post-UPI Mean	0.020	1.205	1.031	6.660
Dep. var mean	0.014	0.819	0.918	6.044
N	428000	428000	428000	428000

Standard errors in parentheses

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

Lenderwise Impact: NTC

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.022***	1.567***	-0.138***	0.055
	(0.003)	(0.203)	(0.037)	(0.368)
R^2	0.772	0.762	0.975	0.980
Pincode FE	Y	Y	Y	Y
Neighbourhood-time-FE	Y	Y	Y	Y
Pre-UPI Mean	0.001	0.023	3.155	25.714
Post-UPI Mean	0.046	3.381	3.094	27.829
Dep. var mean	0.032	2.290	3.114	27.141
N	428000	428000	428000	428000

Standard errors in parentheses

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

Main

Lenderwise Impact: Prime

	(1)	(2)	(3)	(4)
Lender	FinTech		Banks	
Dependent variable	Amt (Million INR)	Act	Amt (Million INR)	Act
High UPI Exposure × Post	0.078***	2.203***	3.327***	21.603***
	(0.015)	(0.261)	(0.345)	(2.443)
R^2	0.577	0.748	0.963	0.958
Pincode FE	Y	Y	Y	Y
Neighbourhood-time- FE	Y	Y	Y	Y
Pre-UPI Mean	0.002	0.032	6.896	39.554
Post-UPI Mean	0.128	4.230	12.503	76.490
Dep. var mean	0.087	2.866	10.680	64.486
N	428000	428000	428000	428000

Standard errors in parentheses

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

Main