Does Open Banking Expand Credit Access?

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Motivation

- Credit growth: A key mandate for any Financial Intermediaries
- Financial Inclusion: Imp. Public policy goal for policymakers and Central Banks. 1.4 billion people lack credit access (World Bank 2022).
- Promise of fintech– can use alternate data to create novel credit scoring models and expand credit access (Berg et. al. 2020; Agarwal et al.2023; Ghosh et.al. 2024)
  - But fintech has not been able to expand financial inclusion(Buchak et al. 2018; Gopal et al.2022; Benetton et. al.2002)
- Can Bank Account with Payment rail help? Open Banking framework shows promise as it increases competition and innovative entry- However limited understanding in credit market expansion

Our focus: Does bank accounts connected by free, interoperable payment rail, and customer driven data sharing through Open Banking framework helps in credit expansion and financial inclusion?

What is open banking (OB)?

- Open Banking is a framework which empowers bank customers to share their financial transactions data from their bank accounts with other financial service providers. (Babina et. al, 2023)
- 49 countries adopted Open Banking. Policy mandate varies by countries
- In UK only 7 largest banks are mandated to share data
- Singapore, USA no explicit mandate yet, industry led mediation
- India fully adopted Open Banking: Customer-permissioned data sharing to any financial institutions (Bank, NBFC, Fintech etc)

Customer is at the heart of Open Banking:

- Financial Inclusion: Leverage real-time digital payment data to expand financial access
- All financial institutions get benefit, thus credit increase may happen across all intermediaries $\rightarrow$ bring competition
- Financial Institutions comes up with new products/innovation

Open Banking (OB): Key aspects and players

- Data access and sharing facilitated through Application Programming Interface (API)
- Reduces cost for (a) customer service, (b) e-KYC verification, (c) financial transactions
- Banks and Financial Institutions: These are the core financial data and services providers.
  - OB empowers bank customer's to share their financial transactions data from their bank accounts with other financial service providers: third-party providers (TPPs)
- Third-Party Providers (TPPs): These are entities that use the open APIs provided by banks to build new financial services and apps. In particular there are Payment initiation service providers who faciliate digital payments

Research Question

India has a unique Open Banking structure: (a) generate real-time verifiable digital transactions data free; (b) customer can share data between any financial intermediaries

- How does Open Banking-based digital payment infrastructure (India's UPI) 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?

What Do We Do?

We collect massive amounts of proprietary data from 6 different sources for this research.

Data-1: Credit Data

- Detail Credit registry data on retail loans from Transunion CIBIL from Q1-2016 to Q4-2019 at the pincode-quarter-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, NBFC, Private Banks, Public Sector banks
  - by borrower type: super-prime, prime plus, prime, near-prime, sub-prime, new-to-credit

Data-2: Digital Transaction

- Monthly digital financial transaction volume aggregated at pincode from 2016 to 2019. Provided by one of the top 5 Payment service provider $\Longrightarrow$ cash-flow based variable generated from real-time payment rail.

What Do We Do?

Data-3: Bank Branch Deposit Data

- Deposit data by bank type and bank branch, by pincode, by year from 2014-2015 from RBI $\Longrightarrow$ used construct the exposure measure used in the empirical strategy.

Data-4: Bank accounts data

- Number Jan Dhan Yojana (JDY) accounts opened, at the pincode-month level from Dept. of Financial Services, Govt. of India
- Objective of Jan Dhan Yojana was to provide banking services to the unbanked population in India. Started in 2014

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.

What Do We Do?

Combining all these datasets, we present five key results:

- Credit market expands due to the Open payment infrastructure powered by bank accounts
- Manyfold increase in credit to underbanked and marginal borrowers
- Fintech leads the growth, although Bank and NBFC credit also grows
- Regions with more JDY account (previosuly unbanked) have increased credit growth led by Fintech
- Credit grows in region with cheap and better internet connectivity

Why should open banking infrastructure affect credit?- Related Literature

Information is the Key

- Information-relationship banking: Chan, Greenbaum,& Thakor, 1986;, Petersen & Rajan, 1995;, Boot& Thakoor, 1997; Granja et al. 2022
- Information-transaction Data Agarwal et al.,2023; Ghosh et 2024; Berg et.al, 2020; Di Maggio et al. 2022
- Banks vs. Fintech Gopal et al.,2022; Buchak et al., 2018, Egan, 2022; Benetton et al. 2022
- Information: Open Banking Babina et al., 2023; He, Huang,& Zhou, 2023; Parlour, Rajan,& Zhu, 2022, Sarkisyan, 2023

Our Contribution

- Impact on credit is theoretically ambiguous!
- Open payment infrastructure $\implies$ Lower credit supply from traditional banks
- Open banking-induced competition $\implies$ innovation by new entrants (better screening technology)
- Our Primary Contribution:
  - Introduce a new channel:
    Power of Bank Accounts added with Digital Payments history and Sharing ability of that data $\implies$ Leads to formal Credit
  - First large sample study to examine the impact of Open banking in the form of open publicly funded digital payment infrastructure on credit markets $\implies$ across institutions, across borrowers.

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

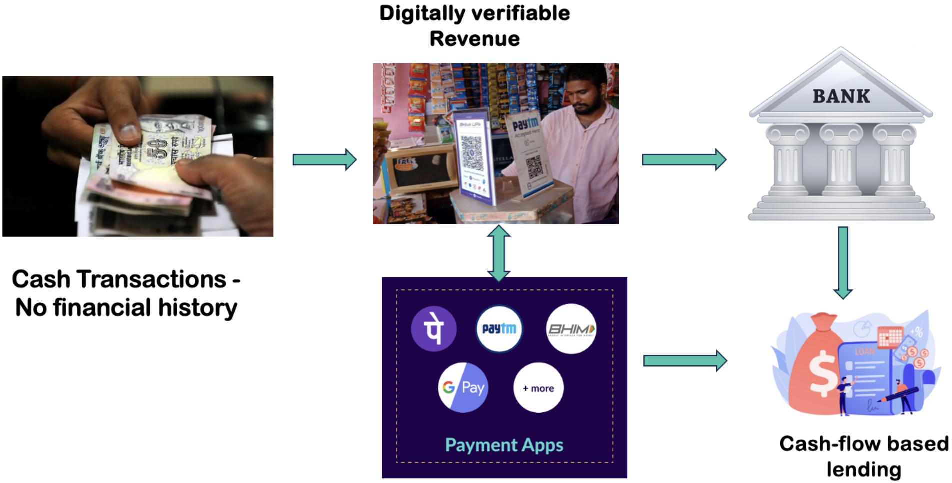
- Globally, policies are still nascent regarding the structure and regulation of Open banking
- "India has become a leader in developing world-class digital public infrastructure (DPI)."–IMF Open Banking Worldwide
- India's publicly funded digital infrastructure (India stack) to spur open banking:
  - 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)

What is the Unified Payments Interface (UPI)?

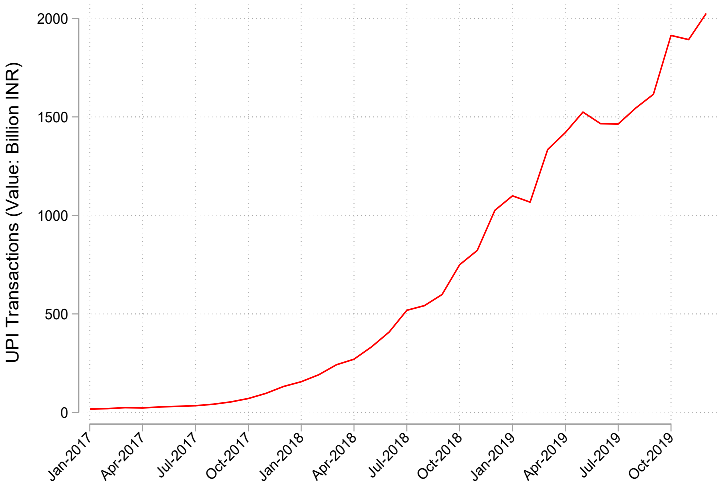
- A payment system built as an interoperable protocol that allows third-party vendors to build apps to provide payments as a service to all customers of participating banks.
- Salient features include:
- Interoperability [customer to merchant to bank to customer]
- Ease of Access [multiple bank accounts into a single mobile application]
- Broad penetration[More than 430 million unique UPI accounts]
- Digital inclusion [Transfer money through mobile 24x7,to any accounts: absolutely free
- Enables real-time zero cost creation of a digital verifiable financial history for all

UPI and Credit



India's Digital Revolution: The Perfect Storm

Phenomenal Growth in UPI



Phenomenal Growth in UPI and Other Digital parameters

Some Statistics: source: NPCI, RBI, MeYti, NSSO, ICE-360, Staista

- 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 (PMJDY) started in 2014

Data:

We collected massive amounts of proprietary data from six different sources.

Data Sources 1 Data Sources 2

Data-1: Credit Data

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Data-2: UPI data

- UPI volume data at the pincode-month from 2016 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 2014-2015 from RBI $\implies$ used construct the exposure measure used in the empirical strategy.

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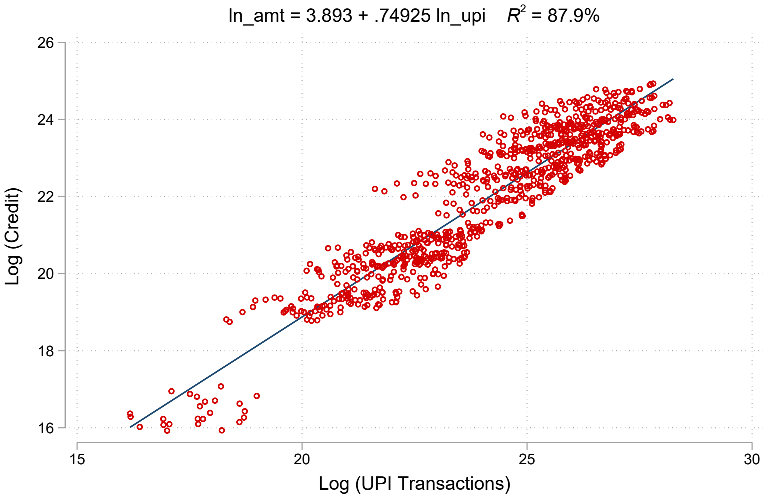
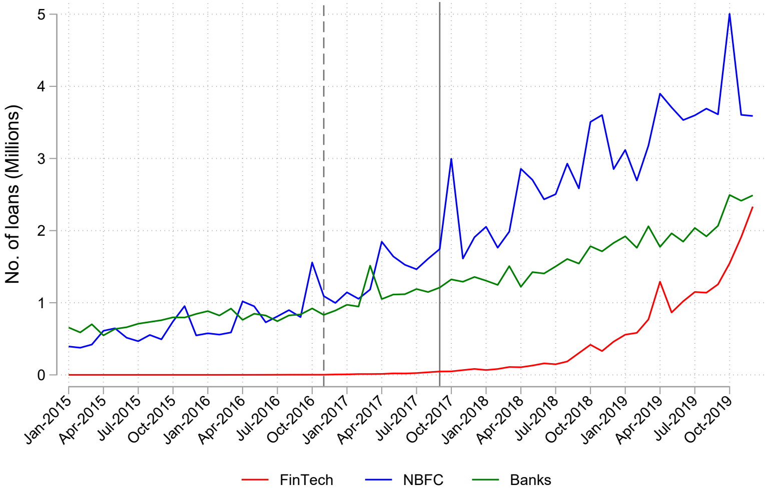
10% increase in UPI payments associated with 7% increase in credit



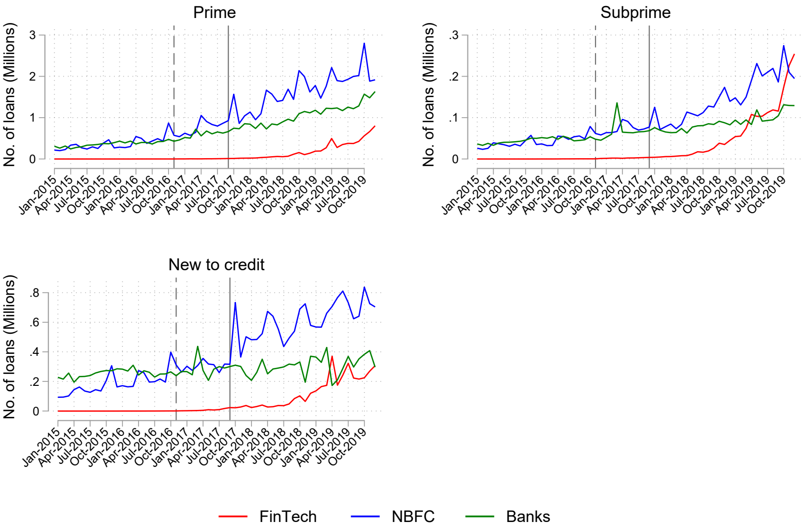
Observations at the state-month level for 2018 to 2020

Lender-wise trends



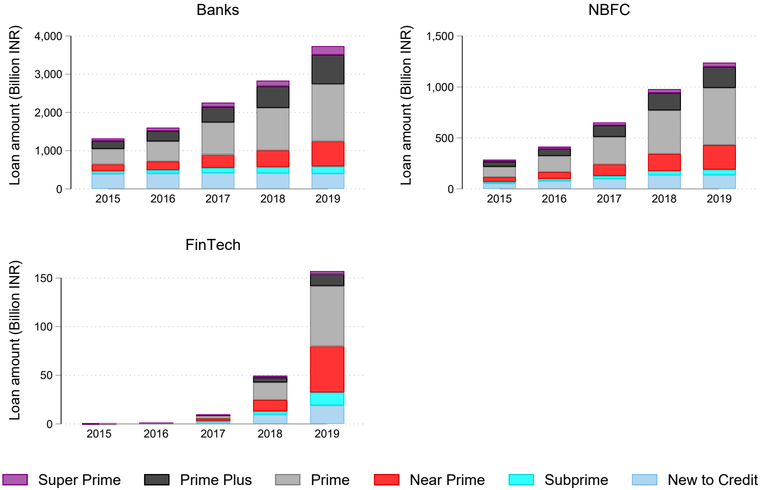
Credit growth across the board for all lenders post Q2 2016 (dashed grey vertical line) when UPI was introduced, but sharper increase post September 2017 (solid grey vertical line) when open banking became stronger through a multi-bank PSP model.

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

Loan composition by credit score and lender



- Credit growth across the board for all lenders.
- Relatively greater tilt towards near-prime, subprime, and New-to-credit in the FinTech loan portfolio.

Identification and Empirical Strategy

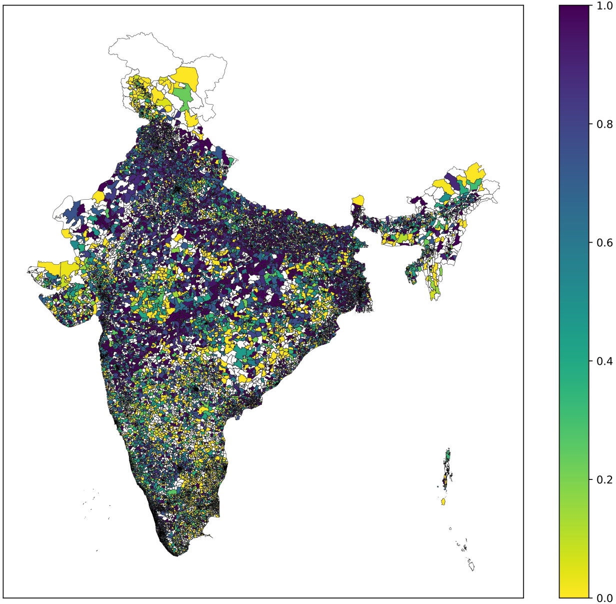
Exploit UPI adoption by banks

- 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 `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.

UPI Exposure: Pincode variation



Comparing Pre- and post- November 2016

High exposure areas see greater increases in credit access.

Score Band	Number of loans (#)						
	Low Exposure			High Exposure			DiD
	Pre	Post	Post-Pre (Level)	Pre	Post	Post-Pre (Level)	High-Low
	Panel A: FinTech						
New-to-credit	0.007	16.870	16.863***	0.016	21.433	21.418***	4.555***
Subprime	0.007	8.418	8.411***	0.012	10.609	10.597***	2.186***
Prime	0.010	24.716	24.706***	0.016	30.867	30.851***	6.145***
	Panel B: Non-FinTech NBFC						
New-to-credit	32.965	97.638	64.673***	43.961	125.050	81.089***	16.417***
Subprime	7.444	23.556	16.111***	9.909	30.683	20.773***	4.662***
Prime	40.545	184.954	144.409***	53.527	237.751	184.224***	39.815***
	Panel C: Banks						
New-to-credit	48.774	54.574	5.800***	65.649	76.931	11.282***	5.482***
Subprime	8.934	16.563	7.628***	11.149	19.101	7.952***	0.324***
Prime	41.815	108.304	66.489***	53.938	146.256	92.318***	25.829***

Empirical Specification: UPI

Effect of exposure on UPI for pincode p in district $d(p)$ in year-quarter t:

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

for pincode p in district $d(p)$ in quarter-year t

- Observations are at the pincode-month level for Q3 2016 to Q4 2019.
- $Y_{pd(p)t}$ is UPI transaction volume and value.
- High Exposure$_p$ is 1 for above median values of UPI exposure.
- $\alpha_{d(p)t}$ refers to the district-quarter-year fixed effect.
- Standard errors are two-way clustered at the pincode and quarter-year level.

Exposure measure and UPI Transactions

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

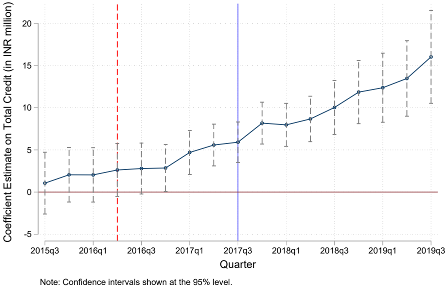
Dependent variable	(1) UPI value (in INR mn)	(2) UPI volume (in '000s)
High Exposure	6.586***	2.941***
	(0.713)	(0.293)
R^2	0.415	0.429
District-quarter FE	Y	Y
Dep. var mean	55.490	24.529
N	112944	112944

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

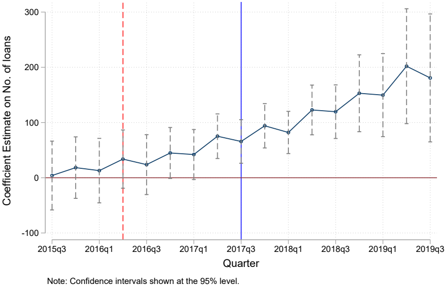
UPI transactions increase by INR 6.586 mn (12% relative to the mean) in pincodes with high exposure.

Impact on Credit Access

All Credit: Temporal Dynamics



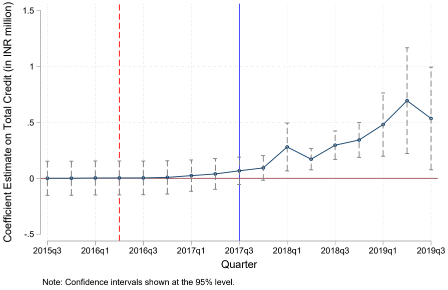
Loan Amount (Million INR)



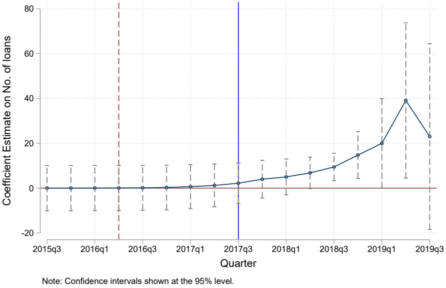
Loan Volume

There is a sharp increase in credit post Q2 2016 (shown by the vertical red line). Credit also increases when an RBI circular made open banking stronger through a multi-bank PSP model in September 2017 (shown by the vertical blue line).

FinTech: Temporal Dynamics



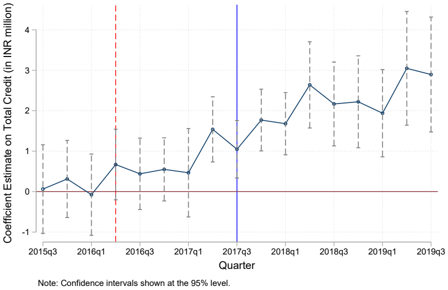
Loan Amount (Million INR)



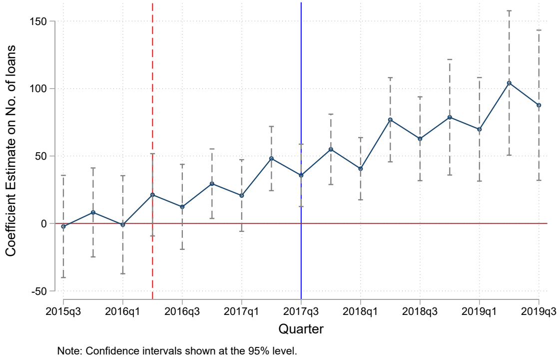
Loan Volume

FinTech credit increases sharply post September 2017 (shown by the vertical blue line) when an RBI circular made open banking stronger through a multi-bank PSP model.

NBFC: Temporal Dynamics

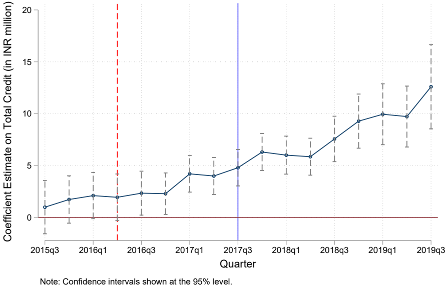


Loan Amount (Million INR)

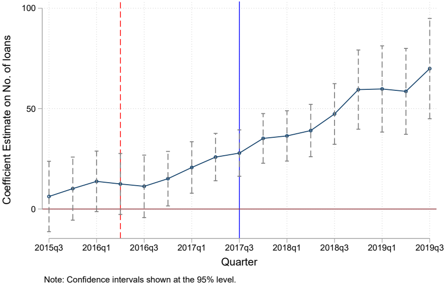


Loan Volume

Banks: Temporal Dynamics



Loan Amount (Million INR)



Loan Volume

Regression Results and treatment effects

Empirical Specification

We estimate the impact on credit using the specification:

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

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 takes a value of 1 from Q3 2016.
- $Y_{pd(p)t}$ is sanctioned amount (in INR million) or accounts.
- $\alpha_{d(p)t}$ and θ_p refer to the district-quarter-year and pincode fixed effects
- Standard errors are two-way clustered at the pincode and quarter level.
- We use this specification for overall credit and different subsamples across borrower types (subprime, new-to-credit, prime borrowers) and lender types (FinTech, NBFCs, and banks).

Impact on Credit: All

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	7.868***	101.033***
	(0.726)	(14.208)
R^2	0.893	0.786
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	32.310	311.622
Post-UPI Mean	69.190	970.591
Dep. var mean	58.126	772.901
N	249200	249200

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

Total effect (Intensive + Extensive) margin: Using the preferred specification in column 2, 24% differential increase in credit value in high-exposure areas with nearly 20% attributable to across-pincode variation (col 1 relative to col 2).
Extensive margin: 32% differential increase in credit volume (number of unique loans) in high-exposure areas using our preferred specification in column 4.

Impact on Credit: Subprime

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	0.309***	4.757***
	(0.038)	(0.982)
R^2	0.874	0.716
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	1.860	18.764
Post-UPI Mean	3.637	54.554
Dep. var mean	3.104	43.817
N	249200	249200

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

- Total effect (Intensive + Extensive) margin: 17% differential increase in subprime credit value in high-exposure areas (within pincodes)
- Extensive margin: 25% differential increase in subprime credit volume (number of unique loans) in high-exposure areas.
- Combined with col 1 $\implies$ jump in small-ticket subprime loans
- Although we cant verify if the same person took multiple loans, so its not Extensive margin in truest sense

Impact on Credit: New-to-credit

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	0.171***	13.584***
	(0.045)	(1.970)
R^2	0.957	0.862
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	8.477	95.815
Post-UPI Mean	9.682	196.595
Dep. var mean	9.320	166.361
N	249200	249200

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

Total effect (Intensive + Extensive) margin:2% differential increase in new-to-credit value in high-exposure areas (column 2). Extensive margin: 14% differential increase in new-to-credit volume (number of unique loans) in high-exposure areas (within pincodes). Combined with col 2 $\implies$ jump in small-ticket new-to-credit loans

Impact on Credit: Prime

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	5.988***	61.476***
	(0.551)	(7.778)
R^2	0.869	0.798
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	17.391	153.735
Post-UPI Mean	44.230	533.653
Dep. var mean	36.178	419.678
N	249200	249200

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

34% increase in volume of prime loans (column 2) and 40% increase in volume (number of unique loans). Prime

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	0.24	0.32	0.17	0.25	0.02	0.14
FinTech Lenders	83.67	216.63	63.33	131.44	37.00	237.82
NBFCs	0.27	0.38	0.23	0.28	0.10	0.24
Banks	0.23	0.21	0.14	0.11	-	0.03

Nearly 217x increase in the number of loans for FinTech lenders compared to much smaller 27% and 23% increase for NBFCs and banks attributable to a smaller base for FinTech lenders in the pre-period. NBFC Banks

Impact on FinTech: All

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	0.251***	11.265***
	(0.046)	(4.256)
R^2	0.523	0.405
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.003	0.052
Post-UPI Mean	1.179	92.720
Dep. var mean	0.826	64.920
N	248920	248920

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

Nearly 84x increase in credit value (total effect), and a 216x increase in credit volume (extensive margin) in high-exposure areas relative to the 24% and 32% increase, respectively, in overall credit.

Impact on FinTech: Subprime

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	0.019***	1.183***
	(0.004)	(0.453)
R^2	0.522	0.414
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.0003	0.009
Post-UPI Mean	0.099	9.547
Dep. var mean	0.069	6.686
N	248920	248920

Standard errors in parentheses

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

Similar increases in subprime loans.

Impact on FinTech: New-to-credit

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	0.037***	2.616***
	(0.005)	(0.687)
R^2	0.579	0.470
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.001	0.011
Post-UPI Mean	0.163	19.215
Dep. var mean	0.114	13.454
N	248920	248920

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

Similar increases in new-to-credit loans.

Impact on FinTech: Prime

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × Post	0.134***	4.009***
	(0.024)	(1.521)
R^2	0.499	0.398
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.001	0.020
Post-UPI Mean	0.582	32.199
Dep. var mean	0.407	22.545
N	248920	248920

Standard errors in parentheses

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

Mechanisms

$\nearrow$ UPI $\implies$ $\nearrow$ lending

How does UPI enable this?

1. 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

2. Jio addressed the "digital divide"

- Rapid geographic coverage of 4G networks
- Jio also enabled UPI growth due to low cost of data

3. 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 (Bharat Pe)

Mechanism 1: JDY bank account holders- Financial formalization

Empirical Specification - Diffference-in-differences-in-differences

We use the following specification:

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

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

- Above median JDY_p takes a value of 1 for above-median value of cumulative pincode-level Jan Dhan Yojana (JDY) accounts as of November 2016.
- $Y_{pd(p)t}$ takes the following values: sanctioned amount (in INR million) and number of accounts.
- $\alpha_{d(p)t}$ and θ_p refer to the district-quarter-year and pincode fixed effects.
- Standard errors are two-way clustered at the pincode and quarter-year level.

High JDY areas see higher increase in credit

All DiDs

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × High JDY × Post	7.460***	127.501***
	(1.233)	(22.923)
High Exposure × Post	4.094***	36.356***
	(0.604)	(9.404)
High JDY × Post	34.765***	657.039***
	(0.904)	(20.351)
R^2	0.895	0.789
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	32.310	311.622
Post-UPI Mean	69.190	970.591
Dep. var mean	58.126	772.901
N	249200	249200

Standard errors in parentheses

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

With 1.29x higher FinTech credit volume in high JDY areas

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × High JDY × Post	0.196***	10.124
	(0.073)	(6.279)
High Exposure × Post	0.152***	6.049**
	(0.033)	(2.373)
High JDY × Post	1.134***	94.074***
	(0.066)	(6.631)
R^2	0.524	0.407
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.003	0.052
Post-UPI Mean	1.179	92.720
Dep. var mean	0.826	64.920
N	248920	248920

Standard errors in parentheses

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

With effects starker for new-to-credit borrowers of FinTech lenders

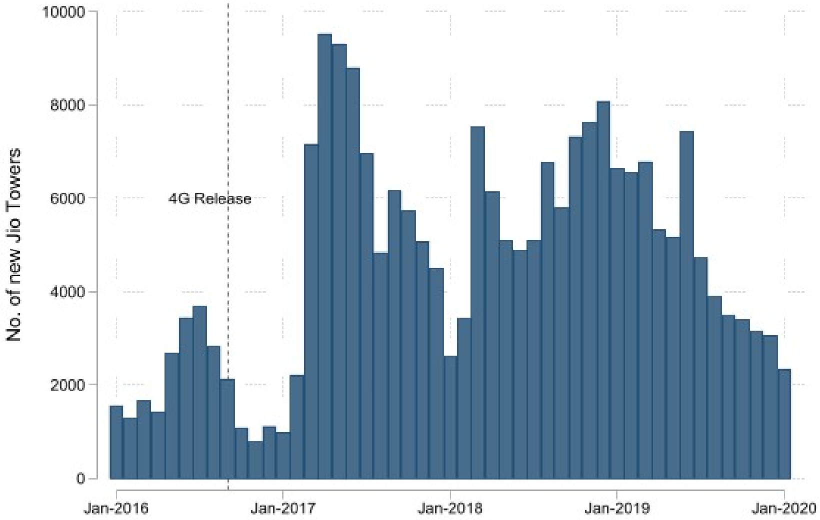
JDY: Fintech + New-to-credit (DDD) DiDs

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
High Exposure × High JDY × Post	0.037***	3.035***
	(0.008)	(1.015)
High Exposure × Post	0.018***	1.078***
	(0.004)	(0.411)
High JDY × Post	0.141***	17.641***
	(0.007)	(1.041)
R^2	0.581	0.472
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.001	0.011
Post-UPI Mean	0.163	19.215
Dep. var mean	0.114	13.454
N	248920	248920

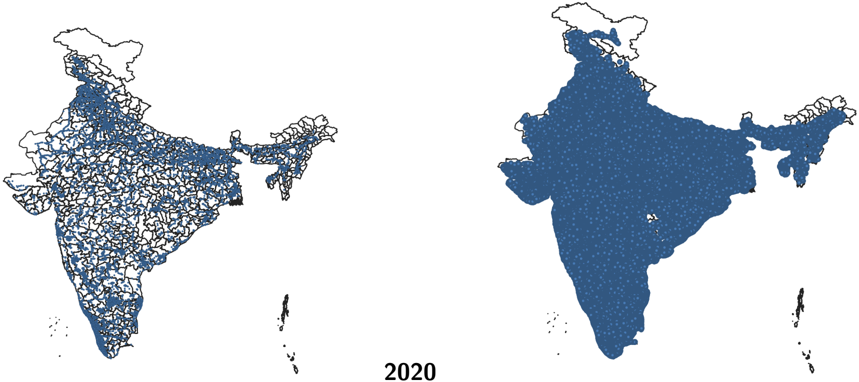
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Mechanism 2: 4G connectivity through Jio

Rapid rollout of 4G Jio Towers starting September 2016



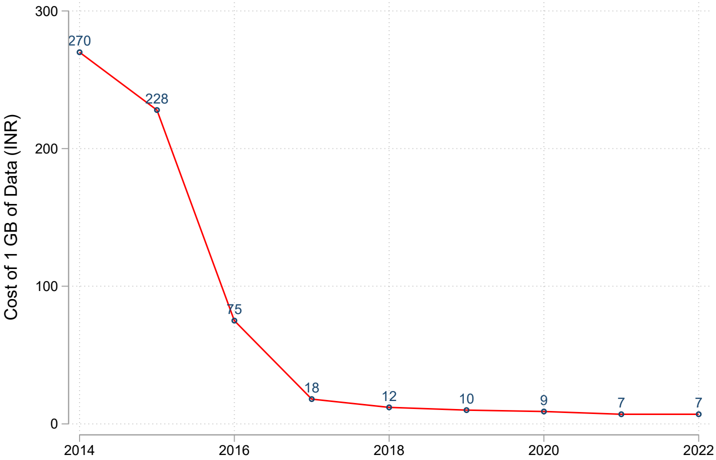
. . . and brought previously excluded areas under 4G



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

To estimate the effect of UPI exposure on and proximity to a Jio tower we run the following specification:

$$
\begin{aligned}
Y_{pd(p)t} = &\alpha_{d(p)t} + \theta_p + \gamma \times \text{Proximity}_{\text{Jio}} \\
&+ \eta \times \text{High Exposure}_p \times \text{Proximity}_{\text{Jio}} + \epsilon_{pd(p)t}
\end{aligned}
$$

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

- Observations are at the pincode-month level from Q3 2016 to Q4 2019.
- $Y_{pd(p)t}$ takes the following values: sanctioned amount (in INR million) and accounts.
- $\alpha_{d(p)t}$ and θ_p refer to the district-quarter-year and pincode fixed effects.
- $\text{Proximity}_{\text{Jio}}$ is the negative log of distance to nearest Jio tower from a pincode in each quarter-year.
- Standard errors are two-way clustered at the pincode and quarter-year level

Across the board increase in high exposure pincodes with proximity to Jio towers

Increase relative to pre-period mean

	All		New-to-credit	
	Vol.	Act.	Vol.	Act.
FinTech Lenders	39.33	133.65	15.00	119.45
NBFCs	0.09	0.13	-	0.06
Banks	0.08	0.07	0.01	0.01

NBFC Banks

Proximity to a Jio Towers increase credit volume and transactions in high exposure areas

FinTech subsample

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	0.118***	6.950***
	(0.025)	(2.337)
$\text{Proximity}_{\text{Jio}}$	-0.145***	-9.039***
	(0.029)	(2.589)
R^2	0.615	0.480
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.003	0.052
Post-UPI Mean	1.179	92.720
Dep. var mean	0.823	64.694
N	174244	174244

Standard errors in parentheses

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

Particularly for FinTech lenders

New-to-credit subsample for FinTech lenders

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	0.015***	1.314***
	(0.003)	(0.376)
$\text{Proximity}_{\text{Jio}}$	-0.019***	-1.801***
	(0.003)	(0.438)
R^2	0.682	0.560
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.001	0.011
Post-UPI Mean	0.163	19.215
Dep. var mean	0.114	13.409
N	174244	174244

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

Stronger impact relative to other internet providers

FinTech subsample

	(1)	(2)
Dependent variable	Amt (Million INR)	Act
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	0.124***	8.661***
	(0.033)	(2.871)
$\text{Proximity}_{\text{Non-Jio}} \times$ High Exposure	-0.013	-2.852
	(0.035)	(3.417)
$\text{Proximity}_{\text{Jio}}$	-0.112***	-6.935**
	(0.030)	(2.780)
$\text{Proximity}_{\text{Non-Jio}}$	-0.225***	-17.425***
	(0.036)	(3.977)
R^2	0.616	0.480
Pincode FE	Y	Y
District-time FE	Y	Y
Pre-UPI Mean	0.003	0.052
Post-UPI Mean	1.179	92.720
Dep. var mean	0.823	64.694
N	174244	174244

Standard errors in parentheses

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

One of the Largest FinTech Lender:
Digital Verifiability of Revenue

Bharat Pe Data Description

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

- 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

Bharat Pe Empirical Specifications

We estimate the impact of UPI exposure or QR 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: Sanctioned loan amount and DRS Score of road-side kiosks.
- X takes the following values: UPI Exposure$_{p(i)}$,QR Transaction count$_{it}$ and Log of QR Transaction Values$_{it}$.
- $\alpha_{s(i)t}$ refer to the state-time fixed effects.
- Standard errors are clustered at the pincode level

Bharat Pe Results - 1

Road-Side Kiosks Only

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Internal Credit Score			Loan Size (in 000's)		
UPI $\text{Exp}_{i,t}$	0.096	-0.136	-0.335*	23.586***	17.131***	14.082***
	(0.187)	(0.174)	(0.180)	(3.909)	(3.586)	(3.580)
Log(QR T.Value)$_{i,t}$		1.349***			22.613***	
		(0.028)			(0.648)	
Log(QR T.Count)$_{i,t}$			1.242***			20.484***
			(0.027)			(0.586)
R^2	0.067	0.194	0.194	0.040	0.130	0.118
State Time FE	Y	Y	Y	Y	Y	Y
Dep Var Mean	14.217	14.208	14.208	92.665	93.405	93.405
N	31553	30862	30862	70813	68475	68475

Standard errors in parentheses

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

- Digital verifiability: QR Transactions positively correlate with loan size and internal credit score.
- As expected, regional UPI exposure is not correlated with internal credit score.

Bharat Pe Results - 2

Road-Side Kiosks Only

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Internal Credit Score			Loan Size (in 000's)		
UPI $\text{Exp}_{i,t}$	0.096	-0.234	-0.240	23.586***	-64.596**	-19.007*
	(0.187)	(1.120)	(0.577)	(3.909)	(25.212)	(10.480)
Log(QR T.Value)$_{i,t}$		1.342***			16.783***	
		(0.084)			(2.082)	
UPI $\text{Exp}_{i,t}$ $\times$ Log(QR T.Value)$_{i,t}$		0.010			8.495***	
		(0.114)			(2.751)	
Log(QR T.Count)$_{i,t}$			1.254***			15.943***
			(0.077)			(1.815)
UPI $\text{Exp}_{i,t}$ $\times$ Log(QR T.Count)$_{i,t}$			-0.017			6.526***
			(0.105)			(2.401)
R^2	0.067	0.194	0.194	0.040	0.130	0.119
State Time FE	Y	Y	Y	Y	Y	Y
Dep Var Mean	14.217	14.208	14.208	92.665	93.405	93.405
N	31553	30862	30862	70813	68475	68475

Standard errors in parentheses

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

Some Important Feature

- Bank accounts with digital payments data history is a powerful combination for credit inclusion
- India's JDY drive helped every household in India to have a bank account
- UPI and Open banking framework led the digital payment revolution in India
- Bank account with customer permissioned digitally verifiable financial transaction data expanded the credit market in India

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?
- We introduce a new channel and examine the impact of public open payment infrastructure $\implies$ first study to do so
- We document an increase in credit access to marginal and unserved borrowers.
- Fintech-led increase in 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!

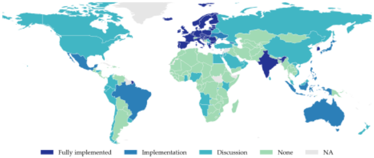
Open Banking: Worldwide Adoption

Babina et al. 2023

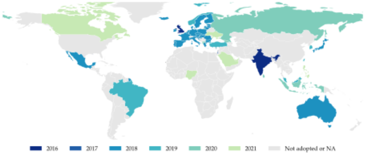
Main

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.

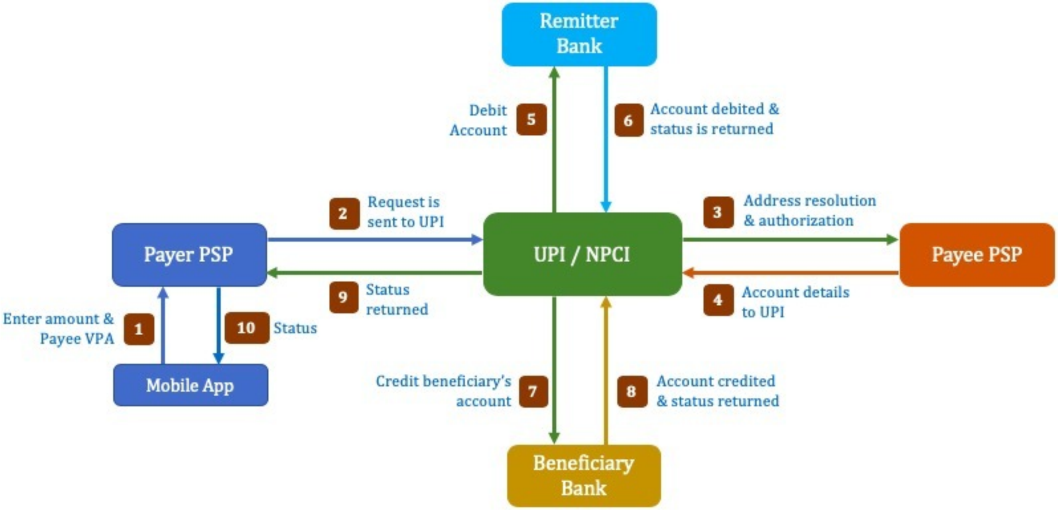


(a) Government open banking policy implementation status

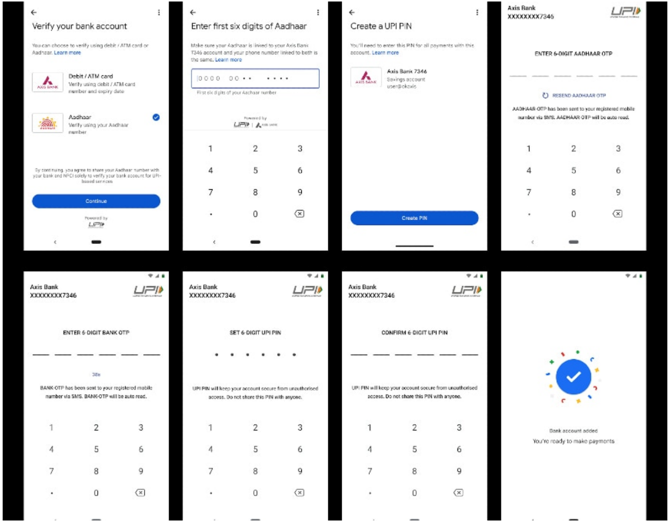


(b) Timeline of open banking adoption

UPI-Payments Flow Chart

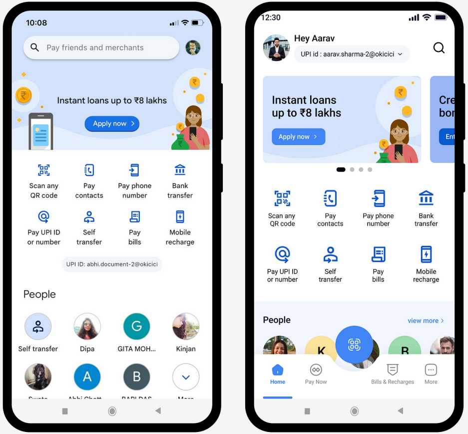


UPI Account Open



Main

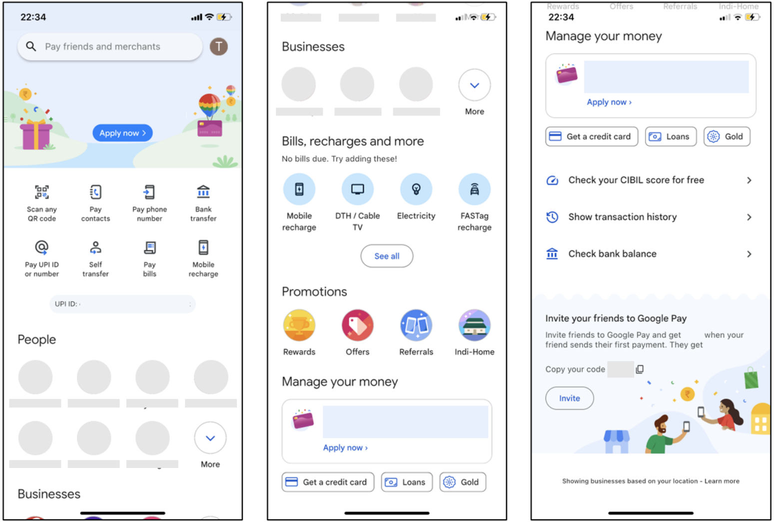
Landing Page-TPP



Old Design **New Design**

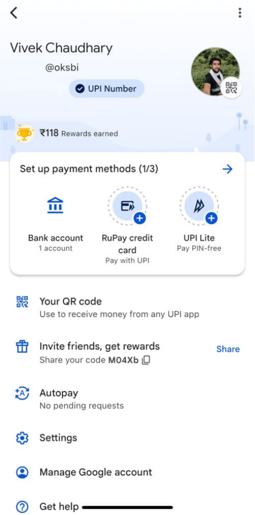
Main

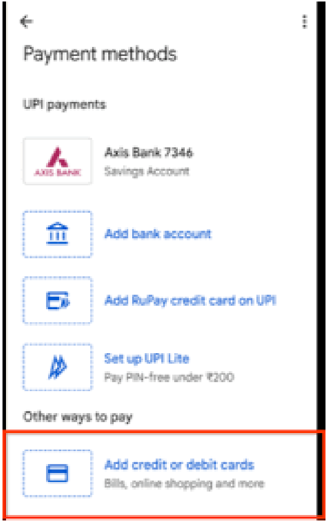
Google Pay Interface

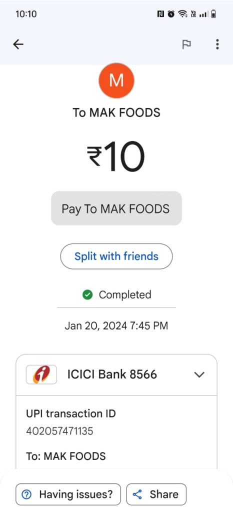


Main

Payment Method







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

Impact on NBFC: All

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	2.363***	1.607***	96.786***	54.161***
	(0.297)	(0.211)	(8.476)	(7.578)
R^2	0.013	0.850	0.019	0.798
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	6.020	6.036	141.940	142.309
Post-UPI Mean	16.762	16.805	541.637	542.982
Dep. var mean	13.540	13.574	421.728	422.780
N	249860	249200	249860	249200

Standard errors in parentheses

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

Main

Impact on NBFC: Subprime

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	0.101***	0.079***	4.662***	2.436***
	(0.018)	(0.017)	(0.480)	(0.428)
R^2	0.007	0.696	0.014	0.771
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	0.348	0.349	8.677	8.699
Post-UPI Mean	0.728	0.730	27.119	27.186
Dep. var mean	0.614	0.616	21.586	21.640
N	249860	249200	249860	249200

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

Main

Impact on NBFC: New-to-credit

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	0.164***	0.111***	16.416***	9.315***
	(0.037)	(0.022)	(1.637)	(1.256)
R^2	0.010	0.797	0.020	0.809
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	1.136	1.139	38.463	38.563
Post-UPI Mean	2.168	2.173	111.343	111.604
Dep. var mean	1.858	1.863	89.479	89.692
N	249860	249200	249860	249200

Standard errors in parentheses

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

Main

Impact on Banks: All

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	7.061***	6.010***	53.606***	35.545***
	(0.936)	(0.514)	(6.290)	(3.567)
R^2	0.009	0.902	0.009	0.896
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	26.273	26.272	169.063	169.261
Post-UPI Mean	51.213	51.207	334.549	334.993
Dep. var mean	43.731	43.726	284.903	285.274
N	249860	249200	249860	249200

Standard errors in parentheses

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

Main

Impact on Banks: Subprime

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	-0.041	0.211***	0.324	1.132***
	(0.052)	(0.027)	(0.358)	(0.166)
R^2	0.007	0.877	0.005	0.876
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	1.510	1.510	10.042	10.056
Post-UPI Mean	2.812	2.808	17.832	17.832
Dep. var mean	2.421	2.419	15.495	15.499
N	249860	249200	249860	249200

Standard errors in parentheses

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

Main

Impact on Banks: New-to-credit

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	0.550***	0.023	5.482***	1.639***
	(0.152)	(0.037)	(1.427)	(0.348)
R^2	0.004	0.953	0.004	0.966
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	7.350	7.337	57.211	57.240
Post-UPI Mean	7.363	7.345	65.752	65.798
Dep. var mean	7.359	7.343	63.189	63.230
N	249860	249200	249860	249200

Standard errors in parentheses

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

Main

High JDY: All (Subsample DID)

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	12.330***	9.086***	210.442***	114.231***
	(2.201)	(1.369)	(30.150)	(28.633)
R^2	0.012	0.903	0.018	0.799
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	46.439	46.392	452.752	454.777
Post-UPI Mean	99.951	99.963	1421.638	1429.104
Dep. var mean	83.898	83.892	1130.972	1136.806
N	124900	123800	124900	123800

Standard errors in parentheses

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

Main

Low JDY: All (Subsample DID)

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	3.869***	4.503***	67.401***	52.165***
	(0.959)	(0.562)	(10.248)	(7.127)
R^2	0.009	0.899	0.021	0.858
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	18.160	18.220	169.427	170.613
Post-UPI Mean	38.364	38.489	515.745	519.450
Dep. var mean	32.303	32.408	411.849	414.799
N	124960	123480	124960	123480

Standard errors in parentheses

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

Main

High JDY: FinTech (Subsample DID)

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	0.435***	0.224**	21.134***	8.334
	(0.068)	(0.093)	(5.895)	(9.004)
R^2	0.009	0.563	0.008	0.435
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	0.004	0.004	0.077	0.077
Post-UPI Mean	1.696	1.709	134.021	135.021
Dep. var mean	1.188	1.198	93.838	94.538
N	124900	123700	124900	123700

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

Main

Low JDY: FinTech (Subsample DID)

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	0.216***	0.192***	11.104***	9.007***
	(0.025)	(0.029)	(1.576)	(1.638)
R^2	0.010	0.596	0.015	0.628
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	0.002	0.002	0.027	0.027
Post-UPI Mean	0.655	0.661	50.793	51.235
Dep. var mean	0.459	0.463	35.563	35.873
N	124960	123280	124960	123280

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

Main

High JDY: FinTech+ New-to-credit (Subsample DID)

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	0.066***	0.043***	5.199***	2.659*
	(0.007)	(0.010)	(0.954)	(1.427)
R^2	0.014	0.620	0.012	0.500
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	0.001	0.001	0.018	0.018
Post-UPI Mean	0.231	0.233	27.374	27.560
Dep. var mean	0.162	0.163	19.167	19.297
N	124900	123700	124900	123700

Standard errors in parentheses

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

Main

Low JDY: New-to-credit+FinTech (Subsample DID)

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
High Exposure × Post	0.027***	0.022***	2.229***	1.622***
	(0.003)	(0.003)	(0.292)	(0.311)
R^2	0.015	0.630	0.020	0.652
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	0.000	0.000	0.005	0.005
Post-UPI Mean	0.094	0.095	10.933	11.009
Dep. var mean	0.066	0.067	7.654	7.708
N	124960	123280	124960	123280

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

Main

Jio and FinTech: Empirical Specification

We capture the heterogeneous impact of digitization on different lenders:

$$\text{Log}(Y_{plit}) = \alpha_{it} + \theta_p + \gamma_l + \beta \times \text{Log}(\text{Dist}_{\text{Jio}}) \times \text{FinTech} + \epsilon_{plit}$$

for pincode p in district i in month t.

- $\text{Log}(Y_{pit})$ takes the following values: log of sanctioned amount and accounts and median amount.
- FinTech is an indicator for Fintech lenders. The comparison group includes banks and non-FinTech NBFCs
- α_{it}, γ_l and θ_p are district-time, lender and pincode fixed effects
- Standard errors are clustered at the pincode level

Main

FinTech vs. Non-FinTech

	(1)	(2)	(3)
Dependent variable	Log(Amt)	Log(Act)	Log(Median Amt)
$\text{Log}(\text{Dist}_{\text{Jio}}) \times$ FinTech	-0.232***	-0.145***	-0.232***
	(0.006)	(0.005)	(0.006)
$\text{Log}(\text{Dist}_{\text{Jio}})$	-0.030***	-0.041***	-0.030***
	(0.009)	(0.009)	(0.009)
R^2	0.684	0.673	0.711
Lender FE	Y	Y	Y
Pincode FE	Y	Y	Y
District-time FE	Y	Y	Y
N	3963834	3973947	3962308

Standard errors in parentheses

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

→ Effects are significantly higher for FinTech lenders that rely more heavily on digital payments transactions (8x in loan volumes and 4x in number of loans)

Main

Effect of Jio

NBFC Subsample

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	3.871***	0.551***	115.359***	18.223***
	(0.269)	(0.112)	(7.845)	(4.205)
$\text{Proximity}_{\text{Jio}}$	9.707***	-1.142***	305.752***	-42.041***
	(0.158)	(0.118)	(4.970)	(4.464)
R^2	0.091	0.916	0.094	0.890
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	6.020	6.020	141.940	141.940
Post-UPI Mean	16.762	16.805	541.637	542.982
Dep. var mean	13.540	13.540	421.728	421.728
N	174902	174440	174902	174440

Standard errors in parentheses

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

Main

Effect of Jio

New-to-credit subsample for NBFC lenders

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	0.316***	0.017	20.102***	2.200***
	(0.025)	(0.017)	(1.295)	(0.688)
$\text{Proximity}_{\text{Jio}}$	0.946***	-0.077***	50.010***	-5.722***
	(0.015)	(0.021)	(0.788)	(0.757)
R^2	0.072	0.815	0.084	0.878
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	1.136	1.136	38.463	38.463
Post-UPI Mean	2.168	2.173	111.343	111.604
Dep. var mean	1.858	1.858	89.479	89.479
N	174902	174440	174902	174440

Standard errors in parentheses

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

Main

Effect of Jio (Horserace)

NBFC lenders

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	2.478***	0.460***	75.155***	16.825***
	(0.282)	(0.156)	(8.490)	(5.682)
$\text{Proximity}_{\text{Non-Jio}} \times$ High Exposure	2.060***	0.108	59.926***	1.134
	(0.271)	(0.136)	(7.929)	(5.187)
$\text{Proximity}_{\text{Jio}}$	5.229***	-0.872***	167.890***	-33.199***
	(0.167)	(0.123)	(5.357)	(4.675)
$\text{Proximity}_{\text{Non-Jio}}$	5.614***	-1.474***	172.831***	-52.130***
	(0.156)	(0.115)	(5.061)	(4.628)
R^2	0.105	0.916	0.108	0.891
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	6.020	6.020	141.940	141.940
Post-UPI Mean	16.762	16.805	541.637	542.982
Dep. var mean	13.540	13.540	421.728	421.728
N	174902	174440	174902	174440

Standard errors in parentheses

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

Main

Effect of Jio

Banks Subsample

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	12.524***	1.985***	95.424***	12.360***
	(0.881)	(0.262)	(5.797)	(1.919)
$\text{Proximity}_{\text{Jio}}$	25.211***	-2.931***	181.800***	-18.982***
	(0.454)	(0.267)	(3.139)	(2.030)
R^2	0.076	0.944	0.088	0.938
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	26.273	26.273	169.063	169.063
Post-UPI Mean	51.213	51.207	334.549	334.993
Dep. var mean	43.731	43.731	284.903	284.903
N	174902	174440	174902	174440

Standard errors in parentheses

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

Main

Effect of Jio

New-to-credit subsample for Bank lenders

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	1.396***	0.039*	17.499***	0.693***
	(0.080)	(0.023)	(0.921)	(0.185)
$\text{Proximity}_{\text{Jio}}$	2.078***	-0.020	26.736***	-0.750***
	(0.042)	(0.031)	(0.463)	(0.207)
R^2	0.055	0.956	0.075	0.971
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	7.350	7.350	57.211	57.211
Post-UPI Mean	7.363	7.345	65.752	65.798
Dep. var mean	7.359	7.359	63.189	63.189
N	174902	174440	174902	174440

Standard errors in parentheses

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

Main

Effect of Jio (Horserace)

Banks subsample

	(1)	(2)	(3)	(4)
Dependent variable	Amt (Million INR)		Act	
$\text{Proximity}_{\text{Jio}} \times$ High Exposure	9.223***	1.771***	64.289***	10.246***
	(0.941)	(0.373)	(5.907)	(2.772)
$\text{Proximity}_{\text{Non-Jio}} \times$ High Exposure	4.914***	0.264	44.891***	2.680
	(0.838)	(0.314)	(5.696)	(2.426)
$\text{Proximity}_{\text{Jio}}$	14.006***	-2.369***	103.404***	-14.157***
	(0.459)	(0.278)	(3.209)	(2.149)
$\text{Proximity}_{\text{Non-Jio}}$	14.048***	-3.006***	98.281***	-25.141***
	(0.420)	(0.237)	(2.955)	(1.913)
R^2	0.086	0.944	0.098	0.938
Pincode FE	N	Y	N	Y
District-time FE	N	Y	N	Y
Pre-UPI Mean	26.273	26.273	169.063	169.063
Post-UPI Mean	51.213	51.207	334.549	334.993
Dep. var mean	43.731	43.731	284.903	284.903
N	174902	174440	174902	174440

Standard errors in parentheses

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

Main