

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

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Nov 2025

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 (Berg, Burg, Gombovic, and Puri, RFS 2020))
 - Even a shallow digital footprint - obtained from just browsing and shopping on the web - has as much predictive power for default as credit bureau score
 - Shallow digital footprint: Simple variables such as Device type, Email provider, Channel, Check-out time, Email error, Name in email, Lower case
 - Cold-start problem: how to facilitate the creation of digital footprints in the first place.
- **Our focus:** Can public provision of cross-platform digital payment infrastructure help?

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**

Flowchart

Opening Page

Interface

Payments Method

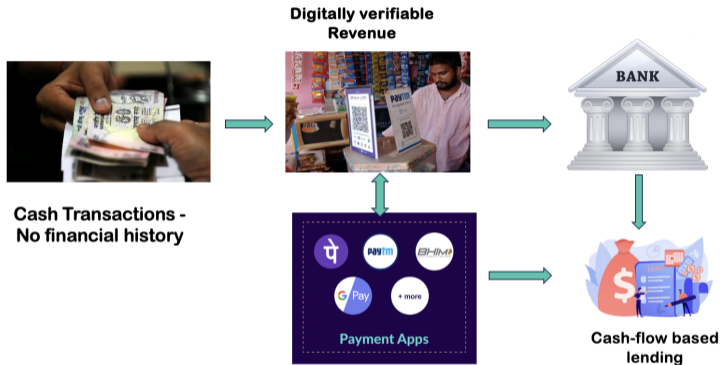
UPI - An open cross-platform payment infrastructure

- 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 → 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 → 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...



- A key precondition for inclusion: the ability of underserved households to **generate verifiable digital payment histories that lenders can use** to assess cash flows.
- By providing a zero-cost, cross-platform payment system, **UPI solved this cold-start problem**, enabling fintechs to expand credit to new-to-credit borrowers.

Research Question

India has a unique digital payment infrastructure which allows interoperable, cross-platform payments and which can costlessly generate real-time verifiable digital transactions data

- How does an open, digital payment infrastructure (India's UPI) affect credit markets? In theory could go either way
 - 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?

Preview of Results

Combining proprietary data from six different sources datasets, we find the following main results: Credit market expands due to the cross-platform digital payment infrastructure.

1. UPI adoption substantially increased financial deepening, measured by the number of loans per capita, particularly for subprime and new-to-credit borrowers.
2. Banks and fintechs responded differently: banks mainly increased lending to prime borrowers, whereas fintechs expanded across all segments—and only fintechs extended credit to new-to-credit customers.
3. Complementarities matter: UPI's impact was strongest in regions with affordable internet access (following Reliance Jio's low-cost 4G rollout) and where households had been recently onboarded into the banking system through the Jan Dhan Yojana (JDY) program.
4. Increased credit access did not come at the cost of higher defaults, suggesting that UPI-enabled digital footprints helped lenders identify underserved but creditworthy 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 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 → Free cross-platform 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

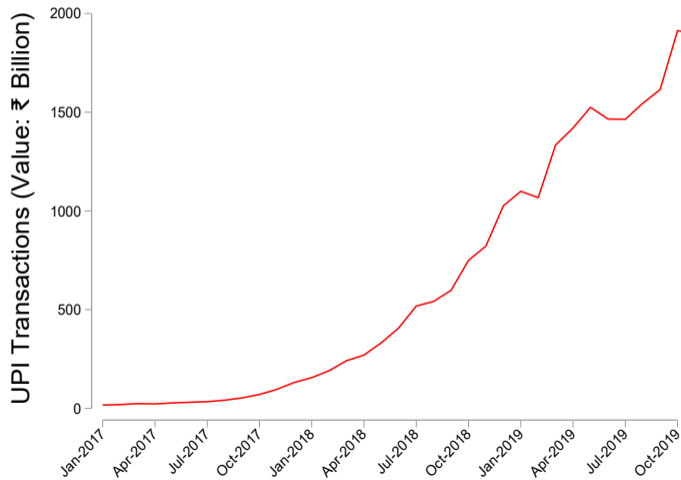
Institutional Details- Unified Payment Interface (UPI)

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 \implies **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 \implies **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 \implies 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

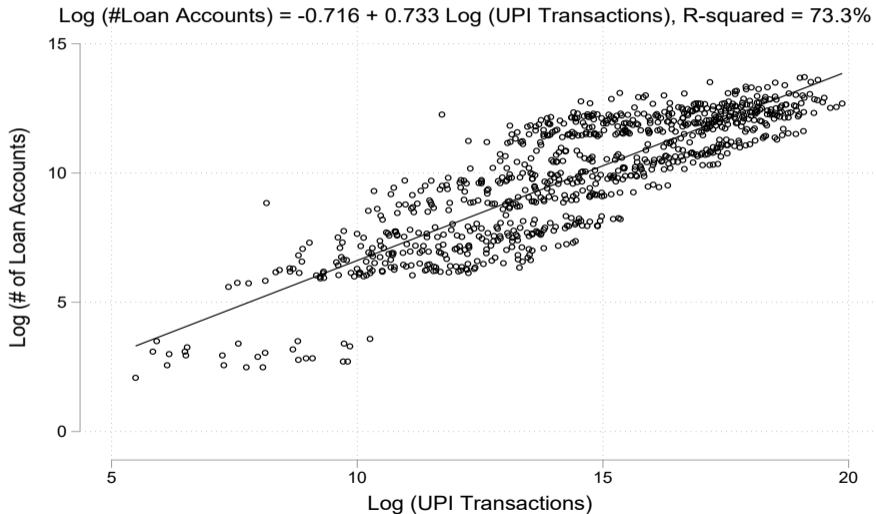
Data-5: Telecom Tower Data

- 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 bureau data if available.

1% increase in UPI payments associated with 0.7% increase in loan accounts



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).
 - Build on UPI adoption measure of Dubey and Purnandam (2024), modify by using pincode level data and all banks.
- Exploit persistent differences in UPI take-up due to strong network externalities in the adoption of digital payments (Higgins, 2020).
- We compute the Exposure for pincode p as:

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

Identification and Empirical Strategy...

- 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.
- Control for time-varying local economic factors using district-by-month fixed effects
 - **Robustness:**
 - **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. **How grids are constructed**
 - 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-by-month fixed effects**
 - We also go further and take an alternate approach that compares only neighboring pincodes that abut each other and compare outcomes within-neighborhood pairs, controlling for pair-by-month fixed effects.

Impact on Credit Access

Temporal Dynamics: Specification

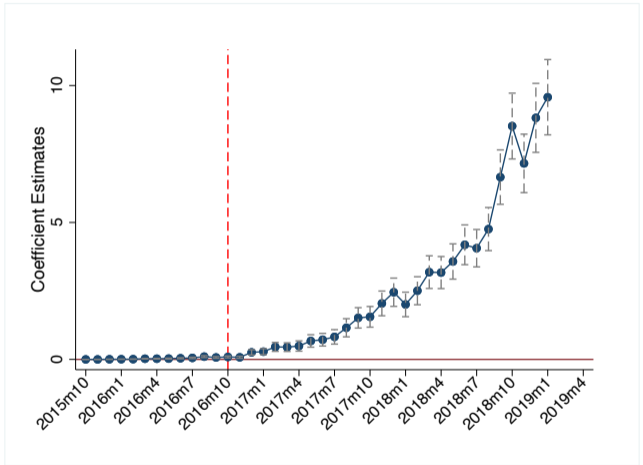
We test for pre-trends using the following event study specification

$$Y_{pt} = \delta_{gt} + \alpha_{d(p)t} + \theta_p + \beta_\tau \times \sum_{\tau} \mathbb{1}_\tau \times \text{UPI Exposure}_p + \epsilon_{pt} \quad (1)$$

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

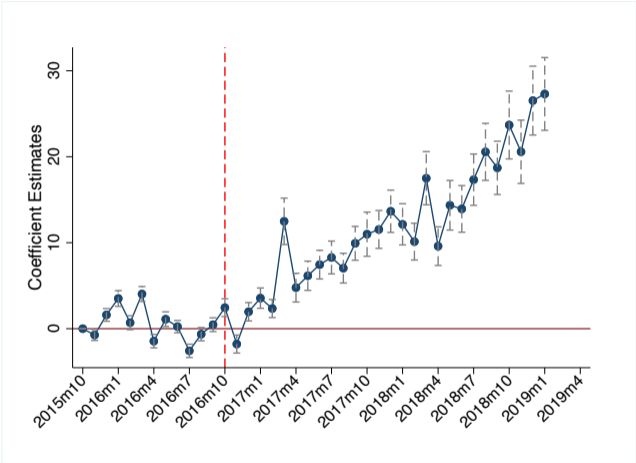
- Observations are at the pincode-month-year level for Oct. 2015-Jan. 2019.
- Y_{pt} is total number of loans or loans per 1000 capita.
- $\alpha_{d(p)t}$, δ_{gt} and θ_p are the district-month-year and pincode FE
- Standard errors are clustered at the pincode level.
- We use this specification for FinTech and Bank loans.

Event Study: FinTech loans



Total number of loans

Event Study: Bank loans



Total number of loans

UPI is a Game-changer: for Whom?

Increase in credit access across financial intermediaries

Increase relative to pre-period mean

	New-to-credit	Subprime	Prime	Total
Fintech	33	20	32	26
Banks	0	0.11	0.26	0.16
Total	0.04	0.17	0.29	0.20

Nearly 26x increase in the number of loans per 1000 capita for FinTech lenders compared to a smaller (but substantial) 16% 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:

$$Y_{pt} = \alpha_{d(p)t} + \delta_{gt} + \theta_p + \beta \times \text{Post}_t \times \text{UPI Exposure}_p + \epsilon_{pt} \quad (2)$$

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_{pt} , is the number of loan originations per 1000 capita.
- $\alpha_{d(p)t}$, γ_{gt} and θ_p are the district-month-year, and pincode FE
- 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 Access: FinTech and Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure × Post	0.922*** (0.146)	0.676*** (0.067)	10.270*** (0.879)	14.674*** (1.284)	0.012*** (0.003)	0.011*** (0.001)	0.161*** (0.019)	0.228*** (0.026)
R ²	0.960	0.926	0.944	0.955	0.938	0.878	0.937	0.950
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	18.227	3.502	28.590	58.621	0.325	0.066	0.549	1.104
Post-UPI Mean	21.339	5.427	52.579	94.325	0.368	0.098	0.964	1.710
Dep. var mean	20.328	4.801	44.783	82.721	0.354	0.088	0.829	1.513
N	508840	508840	508840	508840	508760	508760	508760	508760

Standard errors in parentheses

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

Nearly 20% increase in loans per 1000 capita (total effect), and a 3.69% increase for New-to-credit category in high-exposure areas.

Impact on Credit: FinTech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	0.818*** (0.063)	0.256*** (0.022)	1.023*** (0.079)	2.969*** (0.230)	0.012*** (0.001)	0.004*** (0.000)	0.018*** (0.002)	0.048*** (0.005)
R ²	0.694	0.658	0.701	0.727	0.626	0.570	0.642	0.685
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.018	0.013	0.023	0.070	0.000	0.000	0.001	0.002
Post-UPI Mean	1.960	0.652	2.281	6.911	0.032	0.011	0.040	0.118
Dep. var mean	1.329	0.444	1.547	4.688	0.022	0.007	0.027	0.080
N	504280	504280	504280	504280	504200	504200	504200	504200

Standard errors in parentheses

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

Nearly 24x increase in loans per 1000 capita (total effect), and a 27x increase for New-to-credit category in high-exposure areas.

Impact on Credit: Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	0.080 (0.112)	0.414*** (0.047)	9.160*** (0.797)	11.582*** (1.059)	0.000 (0.003)	0.007*** (0.001)	0.143*** (0.017)	0.181*** (0.021)
R ²	0.966	0.937	0.951	0.966	0.942	0.884	0.943	0.962
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	18.045	3.440	28.447	58.159	0.321	0.065	0.544	1.092
Post-UPI Mean	19.124	4.700	50.021	86.777	0.330	0.086	0.918	1.576
Dep. var mean	18.773	4.291	43.010	77.476	0.327	0.079	0.797	1.419
N	508840	508840	508840	508840	508760	508760	508760	508760

Standard errors in parentheses

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

Nearly 16.58% increase in loans per 1000 capita (total effect), and a near-zero effect for New-to-credit category in high-exposure areas.

Robustness

We conduct a battery of robustness tests, as follows

- With Grid time FE: Analysis is repeated with 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](#)
- With Binary UPI Exposure Measure: Analysis is repeated with High (above median) vs Low (below median) binary UPI exposure measure. [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](#)

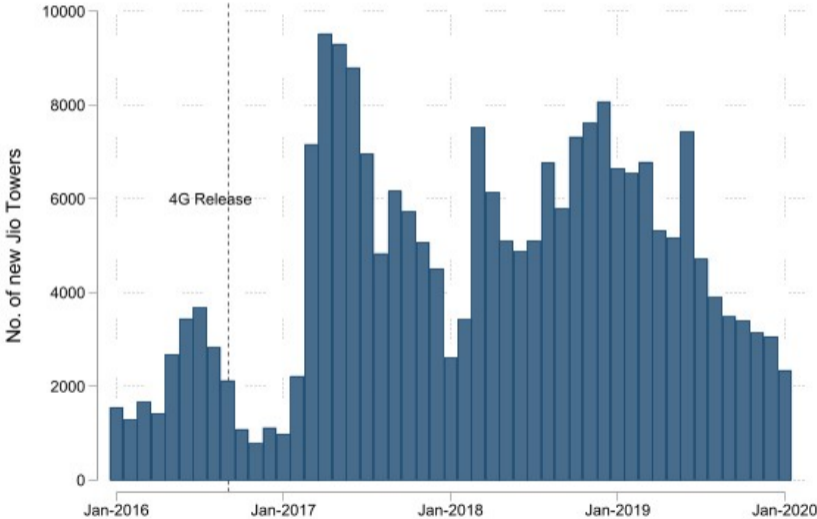
Complementarities

↗ UPI \implies ↗ lending

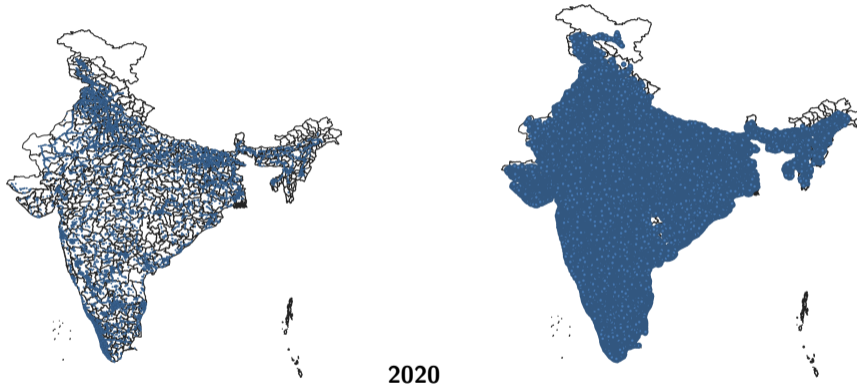
1. Low-cost internet: Jio addressed the “digital divide”
 - Rapid geographic coverage of 4G networks
 - Jio also enabled UPI growth due to the low cost of data
2. Jan Dhan Yojana (JDY) launched in 2014, made previously financially excluded borrowers come under financial inclusion.
 - By July 2016, 99% of Indian households have at least one member with a bank account-Main driver is JDY

Cost of Internet: 4G connectivity through Jio

Rapid rollout of 4G Jio Towers starting September 2016

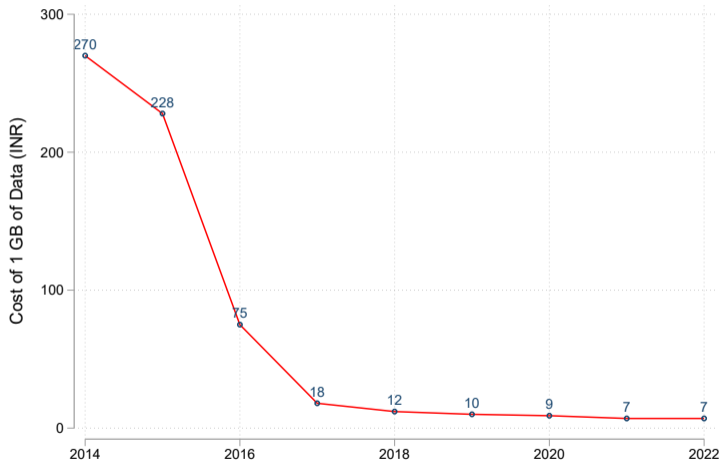


... and brought previously excluded areas under 4G



→ 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,:

$$Y_{pt} = \delta_{gt} + \alpha_{d(p)t} + \theta_p + \gamma \times \text{Early}_{\text{Jio}} \times \text{Post}_t + \chi \times \text{UPI Exposure}_p \times \text{Post}_t + \eta \times \text{Early}_{\text{Jio}} \times \text{UPI Exposure}_p \times \text{Post}_t + \epsilon_{pt}$$

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_{pt} , is the number of loan originations per 1000 capita.
- $\text{Early}_{\text{Jio}}$ 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, and pincode fixed effects
- 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

Impact on Credit: FinTech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
Early _{Jio} × UPI Exposure × Post	0.779*** (0.105)	0.320*** (0.037)	1.159*** (0.130)	3.221*** (0.381)	0.014*** (0.002)	0.006*** (0.001)	0.021*** (0.003)	0.057*** (0.007)
UPI Exposure × Post	0.337*** (0.065)	0.062*** (0.022)	0.317*** (0.075)	0.999*** (0.225)	0.004*** (0.001)	0.001** (0.000)	0.005*** (0.001)	0.014*** (0.004)
Early _{Jio} × Post	0.701*** (0.054)	0.228*** (0.019)	0.886*** (0.067)	2.581*** (0.196)	0.010*** (0.001)	0.003*** (0.000)	0.013*** (0.001)	0.038*** (0.004)
R ²	0.697	0.660	0.704	0.730	0.628	0.572	0.644	0.688
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.017	0.013	0.023	0.069	0.000	0.000	0.001	0.002
Post-UPI Mean	1.960	0.652	2.281	6.911	0.032	0.011	0.040	0.118
Dep. var mean	1.314	0.439	1.529	4.635	0.022	0.007	0.027	0.079
N	504280	504280	504280	504280	504200	504200	504200	504200

Standard errors in parentheses

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

Subsample: Early Jio

Subsample: Late Jio

Impact on Credit: Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
Early _{Jio} × UPI Exposure × Post	-0.048 (0.181)	0.347*** (0.083)	9.860*** (1.300)	12.021*** (1.720)	0.003 (0.005)	0.006*** (0.002)	0.171*** (0.027)	0.219*** (0.035)
UPI Exposure × Post	0.096 (0.116)	0.192*** (0.047)	3.124*** (0.719)	4.180*** (0.955)	-0.001 (0.003)	0.003*** (0.001)	0.040*** (0.014)	0.050*** (0.018)
Early _{Jio} × Post	0.166 (0.110)	0.465*** (0.050)	8.744*** (0.701)	11.349*** (0.934)	-0.005* (0.003)	0.006*** (0.001)	0.126*** (0.014)	0.150*** (0.019)
R ²	0.966	0.937	0.951	0.967	0.942	0.884	0.944	0.962
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	18.036	3.435	28.404	58.088	0.321	0.065	0.544	1.091
Post-UPI Mean	19.124	4.700	50.021	86.777	0.330	0.086	0.918	1.576
Dep. var mean	18.762	4.286	42.943	77.376	0.327	0.079	0.796	1.417
N	508840	508840	508840	508840	508760	508760	508760	508760

Standard errors in parentheses

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

Subsample: Early Jio

Subsample: Late Jio

Robustness: 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 telephone providers in India.

Financial Formalization (JDY accounts): Bank accounts for the unbanked

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

We estimate the differential impact of financial formalization on credit using the specification,:

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

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_{pt} , is the number of loan originations per 1000 capita.
- High JDY_p takes value 1 for pincodes, with above-first tercile cumulative number of JDY bank accounts, as of November 2016.
- 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, and pincode fixed effects

Financial Formalization: Bank accounts for the unbanked

	(1)	(2)	(3)	(4)
Dependent variable:	# of New-to-Credit loans		# of New-to-Credit loans per 1000 capita	
Lender Type:	Fintech	Banks	Fintech	Banks
UPI Exposure \times JDY \times Post	1.029*** (0.104)	-0.173 (0.193)	0.014*** (0.002)	0.003 (0.005)
UPI Exposure \times Post	0.126* (0.075)	0.168 (0.137)	0.003** (0.002)	-0.001 (0.004)
High JDY \times Post	0.984*** (0.055)	0.190 (0.117)	0.008*** (0.001)	-0.008*** (0.003)
R ²	0.699	0.966	0.628	0.942
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.018	18.045	0.000	0.321
Post-UPI Mean	1.960	19.124	0.032	0.330
Dep. var mean	1.329	18.773	0.022	0.327
N	504280	508840	504200	508760

Standard errors in parentheses

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

Benchmarking Aggregate Credit...

- A ₹1.99 million differential increase in loan value in higher exposure pincodes representing an economically significant 22% increase relative to the pre-treatment mean.
- There are important differences in the size of loans offered by banks and fintechs.
 - The average loan size of UPI-led increase in credit for banks is ₹167,329 (= ₹1.938 million/11.582)
 - 9.4x the size of average loans offered by fintechs (₹17,851 = ₹0.053 million/2.969)
 - These results show that fintechs specialize in small-ticket loans to marginal borrowers, while banks offer larger loans to ex-ante included borrowers.
- UPI's introduction led to an overall increase in the volume of credit supplied by both banks and fintechs, with fintechs doing more small-ticket loans.

Impact on Default

Comparing pre and post

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

Score Band	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Low Exposure			High Exposure			DiD High-Low
	Pre	Post	Post-Pre	Pre	Post	Post-Pre	
Fintechs							
New-to-credit	0.064	0.086	0.022*	0.066	0.086	0.019***	-0.003
Subprime	0.135	0.105	-0.031**	0.130	0.108	-0.022***	0.009
Prime	0.043	0.048	0.005	0.026	0.049	0.023***	0.018***
Banks							
New-to-credit	0.016	0.032	0.016***	0.017	0.033	0.016***	0.000
Subprime	0.042	0.064	0.022***	0.043	0.067	0.024***	0.002
Prime	0.011	0.026	0.014***	0.011	0.026	0.015***	0.001

Impact on Default: FinTech

Dependent variable	(1)	(2)	(3)
	Default Rate		
	New-to-credit	Subprime	Prime
UPI Exposure \times Post	-0.053* (0.030)	0.006 (0.056)	0.010 (0.020)
R ²	0.269	0.326	0.258
Pincode FE	Y	Y	Y
District-time FE	Y	Y	Y
Pre-UPI Mean	0.058	0.128	0.028
Post-UPI Mean	0.086	0.105	0.048
Dep. var mean	0.086	0.106	0.048
N	110912	58192	105843

Standard errors in parentheses

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

Impact on Default: Banks

	(1)	(2)	(3)
Dependent variable	Default Rate		
	New-to-credit	Subprime	Prime
UPI Exposure \times Post	0.000 (0.001)	0.001 (0.003)	-0.001 (0.000)
R ²	0.148	0.172	0.157
Pincode FE	Y	Y	Y
District-time FE	Y	Y	Y
Pre-UPI Mean	0.015	0.043	0.010
Post-UPI Mean	0.029	0.066	0.024
Dep. var mean	0.025	0.059	0.019
N	476009	318377	489934

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 a cross-platform public digital payments infrastructure enable credit access?
- Using the universe of credit bureau data in India, we find
 - Digital payment infrastructure (UPI) helps expand credit markets.
 - Credit access for the underserved is led by fintechs, especially for the 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.
- Credit expansion associated with digital payments did not translate into higher default rates – verifiable transaction histories help lenders identify underserved but creditworthy borrowers, expanding access without increasing risk.

Implications for Digital Euro

- We know that digital footprint matters for increased credit across the board but particularly for thin files or people with limited access to credit.
- Access to formal credit is a first order issue even in a developed country like the US!
- Consumers being able to use their digital trail to get loans makes major difference.
- Current proposal of Digital Euro - both offline and online functionality
- Would NOT identify users making or receiving payments to preserve privacy
- But then people currently in the informal sector or with thin credit files do not benefit by access to more credit through the digital trail.
- Design of digital Euro should think through this.
- One potential solution, allow people to populate their information (ON/OFF switch) at their discretion that they can share with lenders – banks or fintechs. Make privacy the discretion of the individual expanding access without increasing risk.

What is incorporated in the Digital Euro - (Berg, Keil, Martini, Puri, 2025)

- How do payment firms' stock prices react to an increase/decrease in the likelihood of Digital Euro's introduction?
- Key idea: Announcement returns of payment firms around central bank communication on Digital Euro
- Use BIS database from Auer et al. (2020) on communication from global central banks on CBDCs.
- Sample period: Jan-2016 to Jun-2022
- Indicator of sentiment towards the introduction of a Digital Euro
- In response to positive speeches on the digital Euro
- Stock prices of European payment firms increase
- Stock prices of U.S. payment firms decrease
- Consistent with geopolitical considerations in designing Digital Euro and desire for strategic autonomy.
- Should also maximize benefit from digital trail

Thank You!

Appendix

Comparing Pre- and post- November 2016

High exposure areas see greater increases in credit access.

Dependent variable:	# of loans						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Low Exposure			High Exposure			DiD
	Pre	Post	Post-Pre	Pre	Post	Post-Pre	High-Low
Panel A: Fintechs							
New-to-credit	0.006	1.263	1.257***	0.029	2.613	2.584***	1.327***
Subprime	0.004	0.405	0.401***	0.021	0.884	0.863***	0.462***
Prime	0.008	1.421	1.413***	0.038	3.089	3.051***	1.638***
Panel B: Banks							
New-to-credit	11.617	12.634	1.016***	24.455	25.588	1.134***	0.117
Subprime	2.111	3.212	1.101***	4.759	6.180	1.421***	0.320***
Prime	16.696	31.476	14.780***	40.113	68.411	28.298***	13.519***

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

Comparing Pre- and post- November 2016 (Contd.)

Dependent variable:	# of loans per 1000 capita						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Low Exposure			High Exposure			DiD
	Pre	Post	Post-Pre (Level)	Pre	Post	Post-Pre (Level)	High-Low
Panel A: Fintechs							
New-to-credit	0.000	0.023	0.022***	0.001	0.042	0.041***	0.018***
Subprime	0.000	0.007	0.007***	0.000	0.014	0.013***	0.006***
Prime	0.000	0.027	0.027***	0.001	0.052	0.051***	0.024***
Panel B: Banks							
New-to-credit	0.235	0.244	0.009***	0.408	0.418	0.009***	0.000
Subprime	0.046	0.065	0.019***	0.084	0.107	0.023***	0.004***
Prime	0.374	0.653	0.278***	0.717	1.187	0.470***	0.191***

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

Summary Statistics (scaled per capita)

	Mean	Median	St. Dev
UPI Measures			
UPI Exposure (N=12,576)	0.47	0.49	0.36
₹UPI in Millions	8.35	2.13	16.24
#UPI Transactions in 1000s	3.67	1.07	6.67
₹UPI per capita	155.54	31.79	362.36
#UPI Transactions per 1000 capita	69.18	15.70	155.92
Total Credit			
Total Loans	82.61	21.00	188.87
Loans per 1000 capita	1.51	0.39	3.58
Total New-to-credit loans	20.31	6.00	41.22
Total New-to-credit loans per 1000 capita	0.35	0.11	0.76
Total Subprime loans	4.80	1.00	11.35
Total Subprime loans per 1000 capita	0.09	0.02	0.22
Total Prime loans	44.71	10.00	108.53
Total Prime loans per 1000 capita	0.83	0.18	2.06
Fintech Credit			
Fintech New-to-credit loans	1.31	0.00	4.43
Fintech New-to-credit loans per 1000 capita	0.02	0.00	0.08
Fintech Subprime loans	0.44	0.00	1.73
Fintech Subprime loans per 1000 capita	0.01	0.00	0.03
Fintech Prime loans	1.53	0.00	5.84
Fintech Prime loans per 1000 capita	0.03	0.00	0.10
Total Fintech loans	4.64	0.00	16.47
Total Fintech loans per 1000 capita	0.08	0.00	0.28
Bank Credit			
Bank New-to-credit loans	18.76	6.00	37.84
Bank New-to-credit loans per 1000 capita	0.33	0.10	0.70
Bank Subprime loans	4.29	1.00	9.89
Bank Subprime loans per 1000 capita	0.08	0.02	0.20
Bank Prime loans	42.94	9.00	103.18
Bank Prime loans per 1000 capita	0.80	0.18	1.96
Total Bank loans	77.38	20.00	174.69
Total Bank loans per 1000 capita	1.42	0.37	3.32
Default rate	0.03	0.00	0.04

Summary Statistics (unscaled)

	Mean	Median	St. Dev
Loan amount (in ₹Million)	12.21	3.65	25.49
Fintech loan amount (in ₹Million)	0.09	0.00	0.34
Bank loan amount (in ₹Million)	12.11	3.63	25.15

Main

Validation of Datasets

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

Main

Balance Table (UPI Exposure)

Main

Dependent Variable	(1)	(2)	(3)
	UPI Exposure		
# New-to-credit accounts	0.0011 (0.0008)	0.0011 (0.0008)	0.0003 (0.0009)
# Subprime accounts	-0.0014 (0.0016)	-0.0017 (0.0016)	-0.0018 (0.0017)
# Prime accounts	0.0009 (0.0008)	0.0010 (0.0008)	0.0011 (0.0008)
# Total accounts	-0.0004 (0.0006)	-0.0004 (0.0006)	-0.0003 (0.0007)
Total population	-0.0284 (0.0387)	-0.0298 (0.0386)	-0.0295 (0.0470)
Night light intensity growth		-0.0414 (0.0370)	-0.0663 (0.0622)
Fraction of households with bank accounts			-0.0090 (0.0373)
Fraction of households with credit cards			0.0769 (0.0943)
Fraction of households with health insurance			-0.0281 (0.0367)
Fraction of households with mobile phones			0.0398 (0.0361)
Unemployment rate			-0.0436 (0.0375)
R ²	0.0091	0.0094	0.0119
District FE	Y	Y	Y
N	12,721	12,444	5,641

Standard errors in parentheses

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

Balance Table (Jio)

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

	(1)	(2)
Dependent variable:	Early _{Jio}	
# New-to-credit accounts	0.001 (0.001)	0.002 (0.002)
# Subprime accounts	-0.001 (0.003)	-0.002 (0.003)
# Prime accounts	-0.001 (0.002)	-0.001 (0.002)
# Total accounts	0.001 (0.001)	0.001 (0.001)
Total Population		-0.350*** (0.090)
Night Light Intensity growth		-0.441*** (0.075)
R ²	0.048	0.060
District-time FE	N	N
N	12477	12755

Standard errors in parentheses

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

UPI-Jio Correlation

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

Dependent variable:	(1) #UPI per 1000 capita	(2) ₹UPI per capita
Early _{Jio}	27.850*** (2.202)	68.940*** (4.887)
R ²	0.400	0.392
District-time FE	Y	Y
Dep. var mean	69.588	156.718
N	238350	238350

Standard errors in parentheses

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

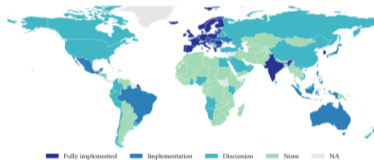
Open Banking: Worldwide Adoption

Babina et al. 2023

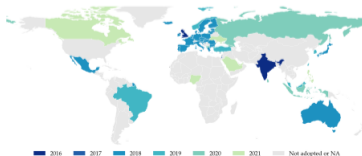
Main

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.

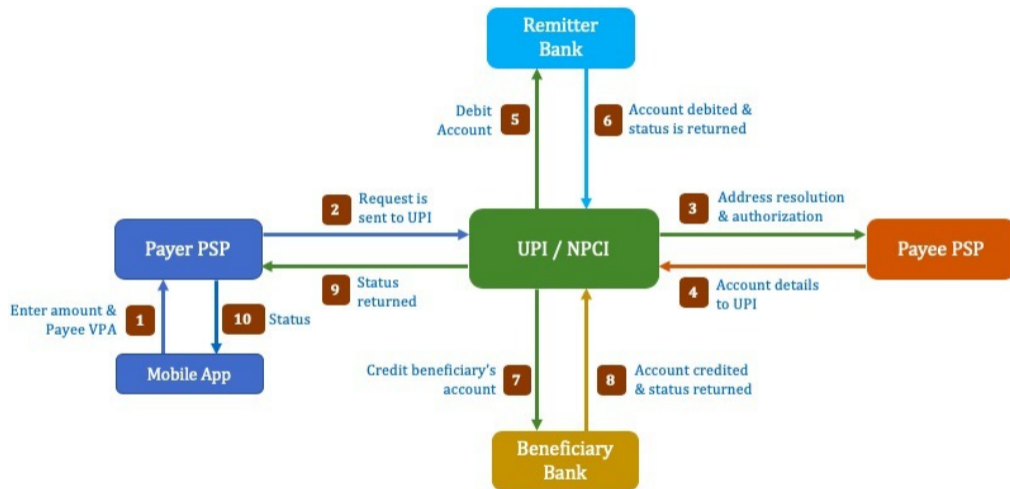


(a) Government open banking policy implementation status

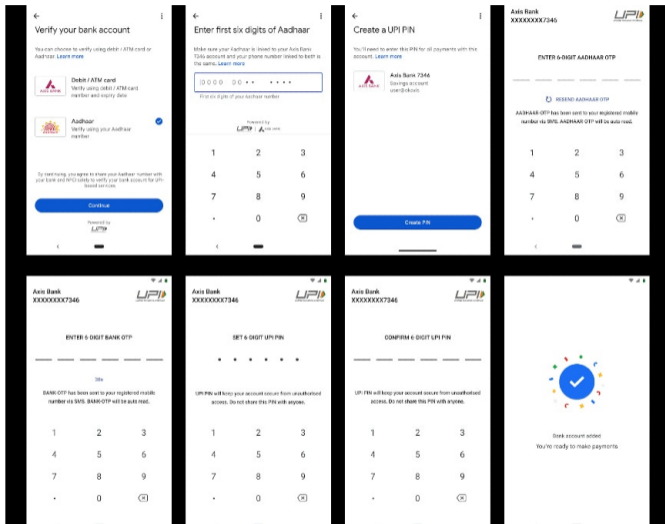


(b) Timeline of open banking adoption

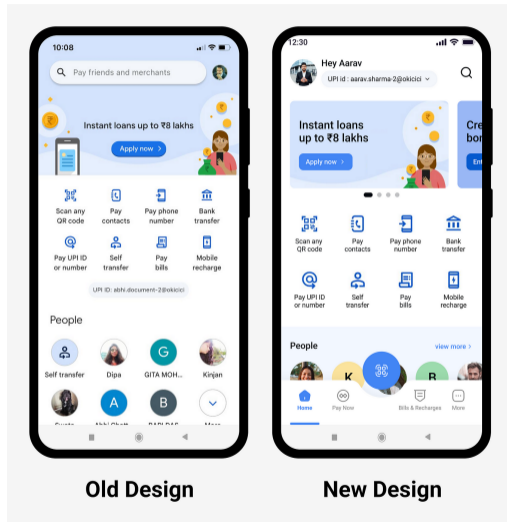
UPI-Payments Flow Chart



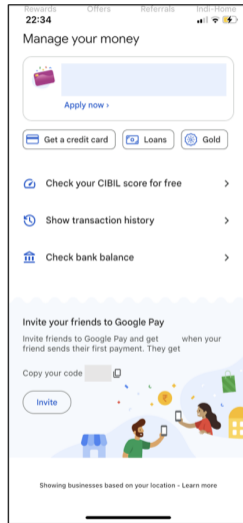
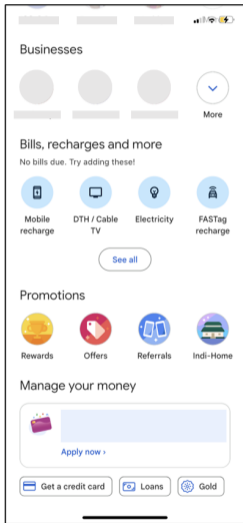
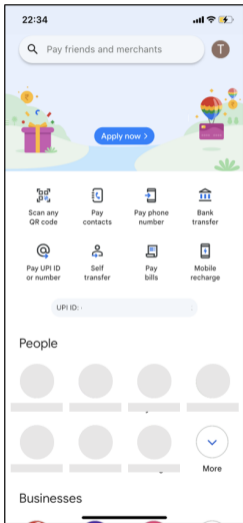
UPI Account Open



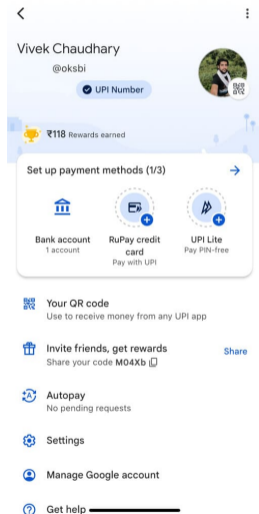
Landing Page-TPP



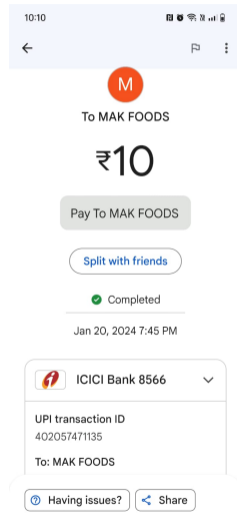
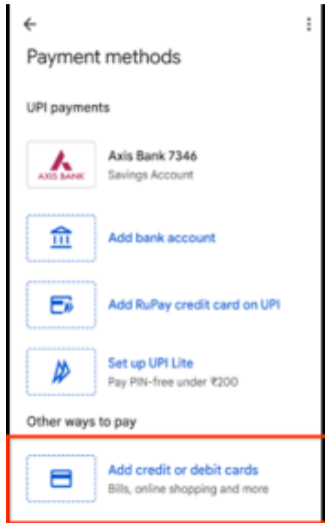
Google Pay Interface



Payment Method



Main



Interoperability

paytm से UPI

Now, Send Money to Any UPI App!

Just Enter Mobile Number
of PhonePe, GPay or Any UPI App User
to Send Money

**Also, Receive Money Directly
in Bank A/c from Any UPI App**

We thank [NPCI](#) for making UPI payments interoperable and more convenient for everyone.

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)

High JDY: Subsample DiD

	(1)	(2)	(3)	(4)
Dependent variable:	# of New-to-Credit loans		# of New-to-Credit loans per 1000 capita	
Lender Type:	Fintech	Banks	Fintech	Banks
UPI Exposure \times Post	1.021*** (0.096)	0.163 (0.178)	0.016*** (0.002)	0.005 (0.004)
R ²	0.738	0.969	0.684	0.956
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.026	25.159	0.001	0.391
Post-UPI Mean	2.617	26.448	0.039	0.401
Dep. var mean	1.775	26.029	0.026	0.398
N	301480	303080	301400	303000

Standard errors in parentheses

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

Low JDY: Subsample DiD

	(1)	(2)	(3)	(4)
Dependent variable:	# of New-to-Credit loans		# of New-to-Credit loans per 1000 capita	
Lender Type:	Fintech	Banks	Fintech	Banks
UPI Exposure \times Post	0.185*** (0.061)	-0.022 (0.122)	0.004** (0.002)	-0.005 (0.004)
R ²	0.672	0.941	0.542	0.903
Pincode FE	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y
Pre-UPI Mean	0.005	7.499	0.000	0.217
Post-UPI Mean	0.985	8.279	0.023	0.226
Dep. var mean	0.667	8.025	0.016	0.223
N	199280	202000	199280	202000

Standard errors in parentheses

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

Impact on Credit (Early Jio Subsample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:					# of loans			
	FinTech				Banks			
	New to Credit	Subprime	Prime	All	New to Credit	Subprime	Prime	All
UPI Exposure \times Post	1.011*** (0.108)	0.353*** (0.039)	1.390*** (0.137)	3.904*** (0.399)	0.113 (0.192)	0.497*** (0.081)	12.188*** (1.415)	15.310*** (1.877)
R ²	0.735	0.701	0.744	0.766	0.970	0.942	0.955	0.969
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.017	0.013	0.023	0.069	18.036	3.435	28.404	58.088
Post-UPI Mean	2.673	0.955	3.387	9.929	27.189	6.886	75.160	128.430
Dep. var mean	1.314	0.439	1.529	4.635	18.762	4.286	42.943	77.376
N	292800	292800	292800	294800	294800	294800	294800	294800

Standard errors in parentheses

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

Impact on Credit (Early Jio Subsample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans per 1000 capita							
	FinTech				Banks			
	New to Credit	Subprime	Prime	All	New to Credit	Subprime	Prime	All
UPI Exposure \times Post	0.017*** (0.002)	0.006*** (0.001)	0.026*** (0.003)	0.069*** (0.008)	0.000 (0.005)	0.009*** (0.002)	0.200*** (0.030)	0.251*** (0.038)
R ²	0.663	0.610	0.680	0.718	0.947	0.893	0.948	0.964
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.000	0.001	0.002	0.322	0.065	0.546	1.094
Post-UPI Mean	0.045	0.016	0.059	0.170	0.470	0.125	1.375	2.326
Dep. var mean	0.022	0.007	0.027	0.080	0.328	0.079	0.798	1.421
N	292800	292800	292800	294800	294800	294800	294800	294800

Standard errors in parentheses

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

Impact on Credit (Late Jio Subsample)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# of loans				# of loans			
	FinTech				Banks			
	New-to-Credit	Subprime	Prime	All	New-to-Credit	Subprime	Prime	All
UPI Exposure \times Post	0.303*** (0.054)	0.055*** (0.015)	0.241*** (0.052)	0.837*** (0.165)	-0.083 (0.099)	0.172*** (0.035)	2.218*** (0.453)	2.802*** (0.612)
R ²	0.565	0.422	0.471	0.563	0.900	0.832	0.881	0.918
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.017	0.013	0.023	0.069	18.036	3.435	28.404	58.088
Post-UPI Mean	0.962	0.230	0.741	2.704	7.892	1.655	15.166	28.946
Dep. var mean	1.314	0.439	1.529	4.635	18.762	4.286	42.943	77.376
N	207840	207840	207840	207840	210520	210520	210520	210520

Standard errors in parentheses

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

Impact on Credit (Late Jio Subsample)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# of loans per 1000 capita							
		FinTech				Banks		
	New to Credit	Subprime	Prime	All	New to Credit	Subprime	Prime	All
UPI Exposure \times Post	0.004*** (0.001)	0.001* (0.000)	0.003*** (0.001)	0.010*** (0.004)	-0.002 (0.003)	0.003** (0.001)	0.031*** (0.012)	0.039** (0.015)
R ²	0.516	0.365	0.449	0.566	0.896	0.773	0.888	0.934
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.000	0.000	0.001	0.002	0.322	0.065	0.546	1.094
Post-UPI Mean	0.016	0.004	0.013	0.046	0.138	0.031	0.293	0.548
Dep. var mean	0.022	0.007	0.027	0.080	0.328	0.079	0.798	1.421
N	207840	207840	207840	207840	210520	210520	210520	210520

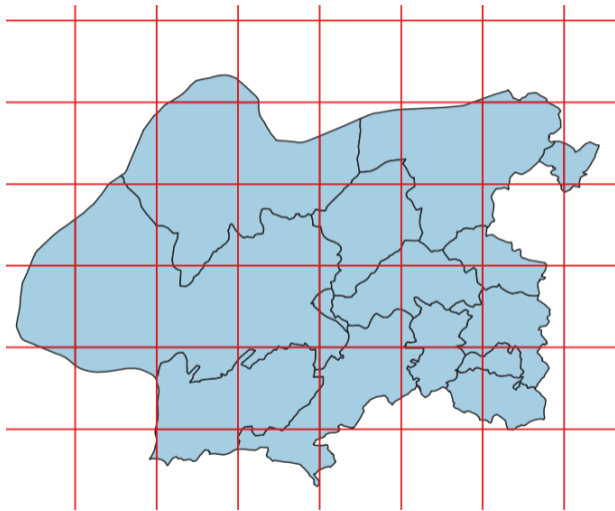
Standard errors in parentheses

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

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.

Example: Jaisalmer, Rajasthan



Robustness with Grid FE

Impact on UPI Transactions

	(1)	(2)	(3)	(4)
Dependent variable:	# UPI in 1000s	₹UPI in Mn.	# UPI per 1000 capita	₹UPI per capita
UPI Exposure	1.430*** (0.139)	3.501*** (0.327)	24.349*** (4.379)	61.966*** (9.762)
R ²	0.586	0.566	0.482	0.479
District-time FE	Y	Y	Y	Y
Grid-time FE	Y	Y	Y	Y
Dep. var mean	3.683	8.387	70.228	157.763
N	231975	231975	231900	231900

Standard errors in parentheses

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

Impact on Credit: FinTech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	0.750*** (0.073)	0.230*** (0.025)	0.905*** (0.088)	2.665*** (0.261)	0.011*** (0.001)	0.004*** (0.000)	0.015*** (0.002)	0.042*** (0.005)
R ²	0.740	0.705	0.755	0.775	0.676	0.620	0.698	0.737
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	0.018	0.013	0.023	0.071	0.000	0.000	0.001	0.002
Post-UPI Mean	1.974	0.659	2.305	6.975	0.033	0.011	0.040	0.120
Dep. var mean	1.338	0.449	1.563	4.731	0.022	0.007	0.027	0.081
N	496640	496640	496640	496640	496600	496600	496600	496600

Standard errors in parentheses

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

Main

Impact on Credit: Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	0.074 (0.128)	0.358*** (0.053)	7.939*** (0.888)	10.072*** (1.183)	-0.002 (0.003)	0.006*** (0.001)	0.116*** (0.019)	0.145*** (0.024)
R ²	0.970	0.944	0.958	0.971	0.947	0.892	0.951	0.966
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	18.140	3.462	28.711	58.611	0.323	0.065	0.550	1.101
Post-UPI Mean	19.232	4.724	50.482	87.471	0.333	0.086	0.928	1.591
Dep. var mean	18.877	4.314	43.406	78.092	0.330	0.079	0.805	1.432
N	501040	501040	501040	501040	500920	500920	500920	500920

Standard errors in parentheses

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

Main

Robustness: Comparing Neighbouring Pincodes
Alternative specification

Impact on UPI Transactions

Dependent variable:	(1) # UPI in 1000s	(2) ₹UPI in Mn.	(3) # UPI per 1000 capita	(4) ₹UPI per capita
UPI Exposure	2.548*** (0.201)	6.156*** (0.484)	23.585*** (4.234)	60.119*** (9.552)
R ²	0.736	0.737	0.749	0.759
Neighbourhood-time FE	Y	Y	Y	Y
Dep. var mean	4.153	9.605	63.878	145.467
N	170100	170100	170000	170000

Standard errors in parentheses

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

Impact on Credit: FinTech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	1.330*** (0.114)	0.413*** (0.038)	1.578*** (0.135)	4.679*** (0.402)	0.011*** (0.001)	0.004*** (0.000)	0.015*** (0.002)	0.042*** (0.005)
R ²	0.868	0.859	0.882	0.889	0.864	0.835	0.883	0.899
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
Neighbourhood-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.023	0.018	0.032	0.095	0.000	0.000	0.001	0.002
Post-UPI Mean	2.604	0.876	3.117	9.330	0.034	0.011	0.042	0.125
Dep. var mean	1.765	0.597	2.114	6.328	0.023	0.008	0.029	0.085
N	428000	428000	428000	428000	427840	427840	427840	427840

Standard errors in parentheses

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

Impact on Credit: Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	-0.134 (0.219)	0.647*** (0.090)	14.594*** (1.310)	17.822*** (1.779)	-0.005 (0.003)	0.007*** (0.001)	0.138*** (0.018)	0.163*** (0.023)
R ²	0.985	0.973	0.979	0.986	0.976	0.950	0.980	0.986
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
Neighbourhood-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	23.386	4.431	37.230	75.862	0.319	0.065	0.551	1.099
Post-UPI Mean	24.962	5.937	66.504	114.373	0.331	0.085	0.941	1.600
Dep. var mean	24.450	5.448	56.990	101.857	0.327	0.078	0.814	1.437
N	428000	428000	428000	428000	427840	427840	427840	427840

Standard errors in parentheses

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

Robustness with control for demonetisation

Impact on Credit: FinTech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	0.762*** (0.063)	0.236*** (0.022)	0.948*** (0.078)	2.752*** (0.228)	0.012*** (0.001)	0.004*** (0.000)	0.017*** (0.002)	0.045*** (0.005)
R ²	0.698	0.660	0.705	0.731	0.628	0.571	0.644	0.688
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Dist _{CC} \times Month Control	Y	Y	Y	Y	Y	Y	Y	Y
Dep. var mean	1.329	0.444	1.547	4.688	0.022	0.007	0.027	0.080
N	504280	504280	504280	504280	504200	504200	504200	504200

Standard errors in parentheses

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

Impact on Credit: Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
UPI Exposure \times Post	0.076 (0.111)	0.388*** (0.046)	8.668*** (0.789)	10.947*** (1.049)	0.000 (0.003)	0.006*** (0.001)	0.137*** (0.017)	0.173*** (0.021)
R ²	0.966	0.937	0.951	0.966	0.942	0.884	0.944	0.962
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Dist _{CC} \times Month Control	Y	Y	Y	Y	Y	Y	Y	Y
Dep. var mean	18.773	4.291	43.010	77.476	0.327	0.079	0.797	1.419
N	508840	508840	508840	508840	508760	508760	508760	508760

Standard errors in parentheses

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

Robustness with Binary High UPI Exposure

Impact on UPI Transactions

Dependent variable:	(1) # UPI in 1000s	(2) ₹UPI in Mn.	(3) # UPI per 1000 capita	(4) ₹UPI per capita
High UPI Exposure	1.481*** (0.092)	3.659*** (0.221)	21.170*** (2.554)	53.115*** (5.769)
R ²	0.515	0.494	0.400	0.394
District-time FE	Y	Y	Y	Y
Dep. var mean	3.677	8.373	69.335	155.833
N	238350	238350	238300	238300

Standard errors in parentheses

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

Impact on Credit: FinTech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
High UPI Exposure \times Post	0.823*** (0.054)	0.264*** (0.019)	1.027*** (0.067)	3.010*** (0.196)	0.011*** (0.001)	0.004*** (0.000)	0.015*** (0.001)	0.041*** (0.004)
R ²	0.695	0.658	0.702	0.728	0.627	0.570	0.642	0.686
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	0.018	0.013	0.023	0.070	0.000	0.000	0.001	0.002
Post-UPI Mean	1.960	0.652	2.281	6.911	0.032	0.011	0.040	0.118
Dep. var mean	1.329	0.444	1.547	4.688	0.022	0.007	0.027	0.080
N	504280	504280	504280	504280	504200	504200	504200	504200

Standard errors in parentheses

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

Impact on Credit: Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	# of loans				# of loans per 1000 capita			
Borrower Category:	New-to-Credit	Subprime	Prime	Total	New-to-Credit	Subprime	Prime	Total
High UPI Exposure \times Post	-0.071 (0.102)	0.390*** (0.040)	9.091*** (0.704)	11.214*** (0.940)	-0.001 (0.002)	0.006*** (0.001)	0.123*** (0.013)	0.156*** (0.017)
R ²	0.966	0.937	0.951	0.966	0.942	0.884	0.943	0.962
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y
District-time FE	Y	Y	Y	Y	Y	Y	Y	Y
Pre-UPI Mean	18.045	3.440	28.447	58.159	0.321	0.065	0.544	1.092
Post-UPI Mean	19.124	4.700	50.021	86.777	0.330	0.086	0.918	1.576
Dep. var mean	18.773	4.291	43.010	77.476	0.327	0.079	0.797	1.419
N	508840	508840	508840	508840	508760	508760	508760	508760

Standard errors in parentheses

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

Robustness for Digital Verifiability of Cash flows

Subsample of Loans with Internal Credit Scores

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

Standard errors in parentheses

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