Can Cashless Payments Spur Economic Growth?

Tamanna Singh Dubey and Amiyatosh Purnanandam

Stephen M. Ross School of Business, University of Michigan

May, 2024

Motivation

- Global interest in instant digital payment systems: FedNow, UPI, Pix.

Motivation

- Global interest in instant digital payment systems: FedNow, UPI, Pix.

- Can means of payment affect real outcomes?
  - Old debate on the role of money in economic output (Lucas and Stokey, 1987; Woodford, 03)

Motivation

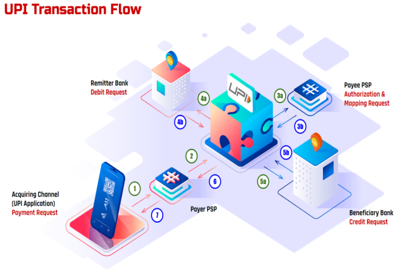
- Global interest in instant digital payment systems: FedNow, UPI, Pix.
- Can means of payment affect real outcomes?
  - Old debate on the role of money in economic output (Lucas and Stokey, 1987; Woodford, 03)
- Digital payments versus cash
  - Transactions cost
    - Lower cost of receiving/sending payments (speed, cost, safety, supply chain efficiency)
  - Credit constraint
    - Improved information for credit creation (screening cost)
    - Enhanced contracting space (tailored to cash flows)
    - Improved enforceability of credit contracts (monitoring cost)

Digital Payments in India

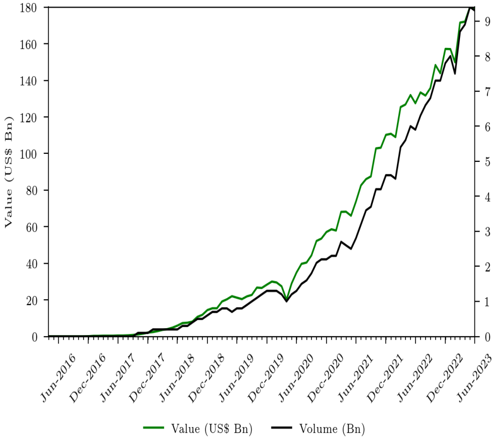
Aadhaar Card	JanDhan Scheme	UPI
2010	2014	2016
Unique Identity Card	**Bank Accounts**	**Digital Payments**
1.2 billion covered	0.5 billion A/Cs	>9 billion transactions/month

Digital Payments in India

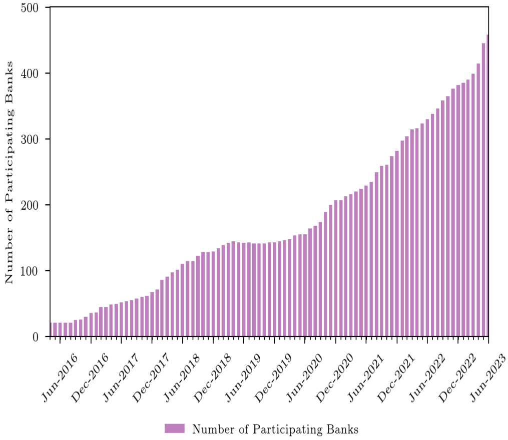
Aadhaar Card	JanDhan Scheme	UPI
2010	2014	2016
Unique Identity Card	**Bank Accounts**	**Digital Payments**
1.2 billion covered	0.5 billion A/Cs	>9 billion transactions/month



Growth of Digital Payments: Volume of Payments & Number of Banks

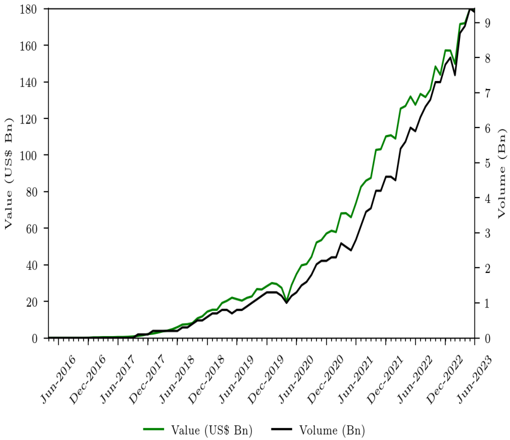


(a) Digital Payments

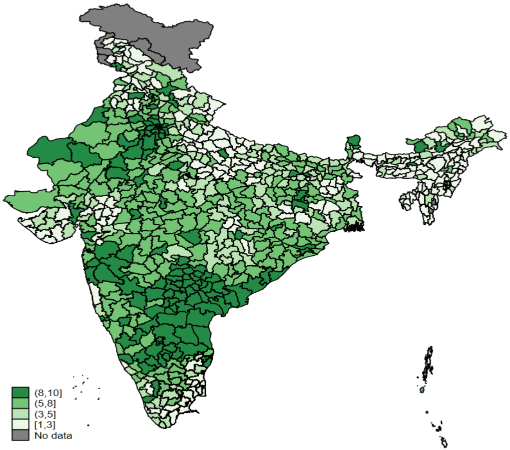


(b) Number of Banks on UPI

Growth of Digital Payments in India: District-level Variation

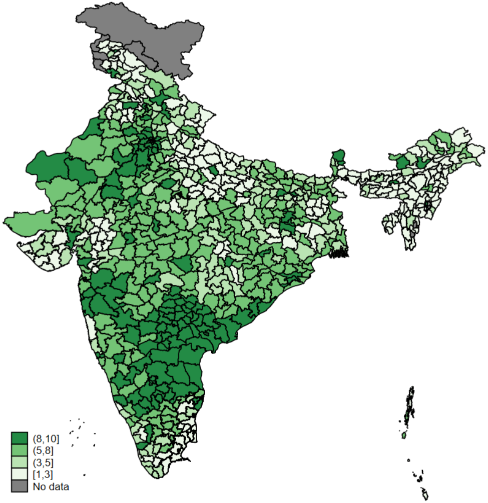


(a) Digital Payments

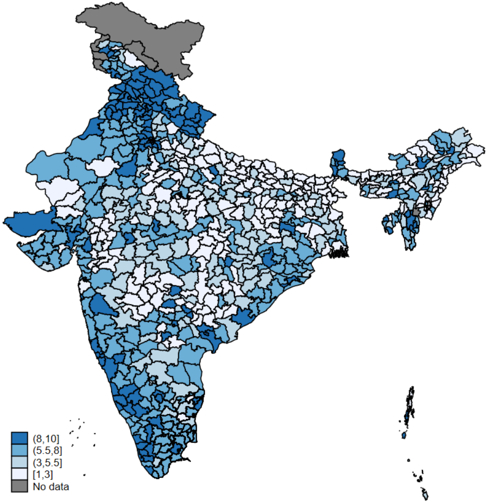


(b) Average Digital Payments Per Person

Geographic Distribution of Digital Payments & Bank Branches



(a) Average Digital Payments Per Person



(b) Bank Branches Per Person

Data

- **Consumer Pyramids Household Survey (CPHS) conducted by Center for Monitoring Indian Economy (CMIE):**
  - Household-level survey data of over 200,000 unique households 3 times a year (2014-2022)
  - Includes demographic, employment, income and expenditure data
- **District-level UPI transactions data by PhonePe:**
  - 2018 Q1 to 2022 Q4, available at quarterly frequency
  - The transactions data is provided by PhonePe, the largest third-party app provider on UPI platform with over 50% market share
- **Reserve Bank of India:**
  - Bank branch data
  - District-quarter credit data
- **IMF:**
  - Nightlight data

Measurement & Base Model

- Main Economic Outcomes:
  - Income of the household: log(income)
  - Business ownership: (a) reported business income, (b) occupation as entrepreneur
  - Business Income: log of business income (Y) modified as per Chen & Roth (2023)
    - mY=0, Y=0
    - mY=log(Y/Y_min), if Y $>$ 0

- Other Measures: Credit, Nightlight, Durable goods purchase

- Base Model: household *i* in district *d* in quarter *t*:

$$y_{idt} = h_i + yq_t + u_i \times yq_t + \beta \times log(digital)_{d,t-1} + \epsilon_{idt}$$

summary descbars

Base Model

$$y_{idt} = h_i + yq_t + u_i \times yq_t + \beta \times log(digital)_{d,t-1} + \epsilon_{idt}$$

Table: Cashless Payments and Outcomes: Panel Data

	(1) Income	(2) Bus(Y/N)	(3) Bus Inc	(4) Entr(Y/N)	(5) Income
Lagged Cashless Payments	0.0868***	0.0122**	0.1688***	0.0299***	0.0943***
	(0.0112)	(0.0049)	(0.0540)	(0.0030)	(0.0105)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Urban x Year-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	Entrepreneurs
Nobs	2,209,164	2,209,164	2,209,164	2,209,164	592,443
Adjusted R-squared	0.558	0.499	0.511	0.494	0.662

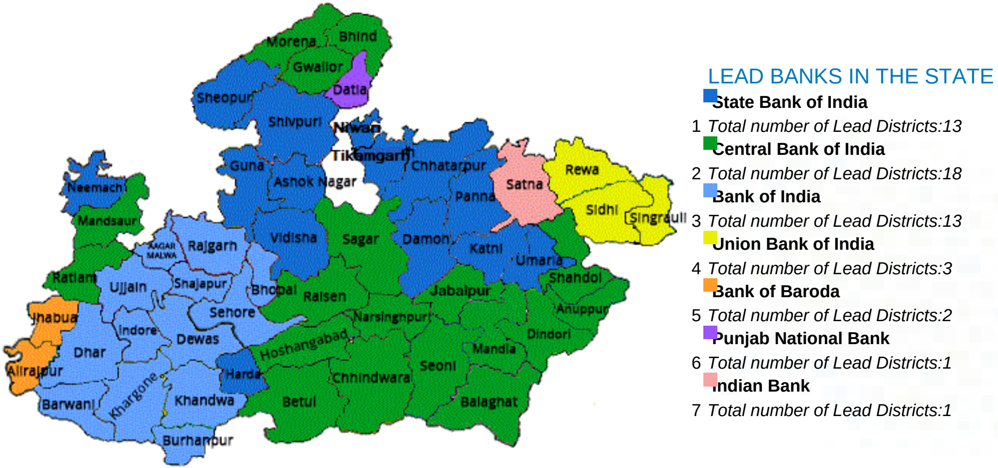
standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Key Identification Strategy: Lead Bank System in India

Lead Banks in a District: System set-up after 1969 nationalization of banks. Still dominant.

lead

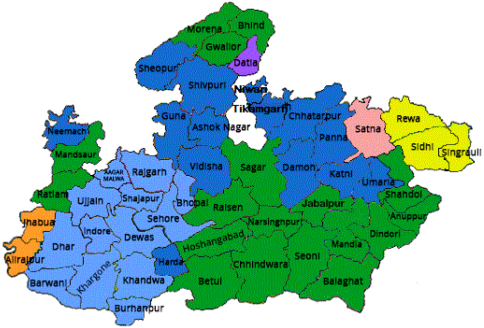


Lead Bank Timing

Early Adopters	Demonetization	Late Adopters
Aug-Nov 2016	Nov 2016	Dec 2016-April 2017
CBI (Green)		BoI (Light Blue)

Lead Bank Timing

Early Adopters	Demonetization	Late Adopters
Aug-Nov 2016	Nov 2016	Dec 2016-April 2017
CBI (Green)		BoI (Light Blue)



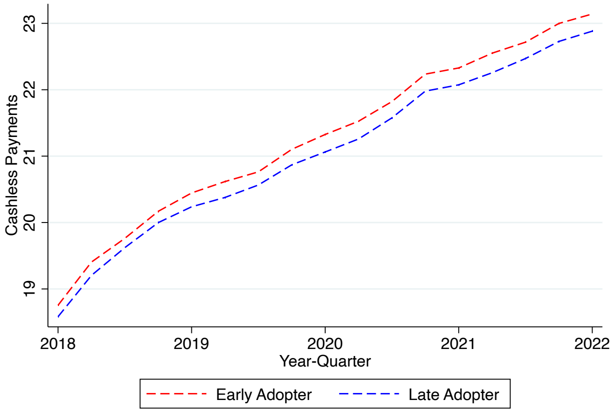
- National banks: participation unlikely driven by changes in local economic conditions.
- Stickiness in tech adoption: Mishra, Prabhala, Rajan (2022).
- Demonetization was a complete surprise.
- Network externality in tech adoption [Crouzet, Gupta, Mezzanotti (2023), Higgins (2023)]
  - initial condition matters a lot.

adoption

Difference-in-Differences Design

- Compare outcomes across early and late districts before and after 2016.
- Districts matched on the following criteria as of 2016:
  - Same state
  - Per capita bank branches
  - Literacy rate
  - Population
  - Bank strength

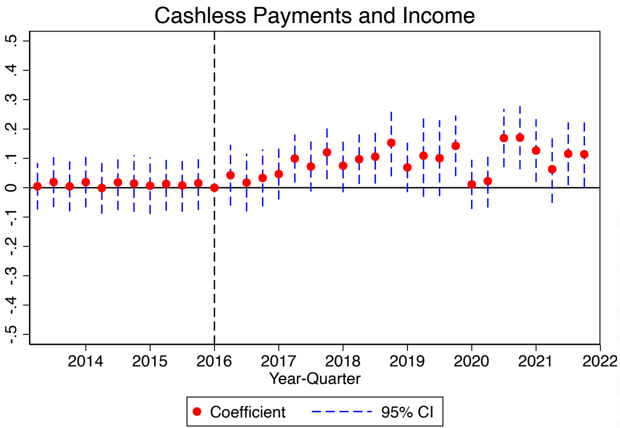
Digital Payments: Early vs. Late Districts



Note: log scale; quarterly data

- 15-25% difference in volume of digital payments.

Income Across Early vs. Late Districts



$$y_{idst} = h_i + yq_t + u_i \times yq_t + s_i \times yq_t + demo_d \times yq_t + \sum_{\tau} (yq = \tau) \times \beta_\tau \times early_d + \epsilon_{idst}$$

Difference-in-Differences Estimates: Matched Sample

Table: Cashless Payments and Outcomes: Early vs. Late Adopters

Outcome Across Early & Late Districts

	(1) Income	(2) Bus(Y/N)	(3) Bus Inc	(4) Entr(Y/N)	(5) Income
Early x Post	0.0785***	0.0103*	0.1265**	0.0243***	0.0497***
	(0.0141)	(0.0055)	(0.0544)	(0.0035)	(0.0152)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
State x Yr-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Urban x Yr-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demonetization x Yr-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	Entrepreneurs
Nobs	936,842	936,842	936,842	936,842	219,788
Adjusted R-squared	0.506	0.353	0.370	0.407	0.637

standard error in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

IV

Identification with Across-Occupation Variation in Outcomes

- Exploits within-district-year-quarter variation across households who are likely to be impacted differently in terms of frictions alleviated by digital payments

- **Within-District-YQ Estimates:**
    - Self-employed households vs. others
- Additionally, in self-employed category, focus on Hawkers/ Small Traders
    - Typically have lower collateral and face relatively tighter credit constraints

Figure 4: Hawker with QR code

Within-District-Year-Quarter Estimates

$$y_{idt} = h_i + dyq_{dt} + \beta \times self_{i,pre} + \theta \times self_{i,pre} \times log(digital)_{d,t-1} + \epsilon_{idt}$$

Table: Effects For Self-Employed Households

Effects For Self-Employed Households

	(1)	(2)	(3)	(4)
	Income	Income	Income	Income
Self-Employed X Lagged Cashless Payments	0.0507***	0.0700***	0.0538***	0.0208***
	(0.0015)	(0.0027)	(0.0065)	(0.0033)
Household Fixed Effects	Yes	Yes	Yes	Yes
District-Year-Qtr Fixed Effects	Yes	Yes	Yes	Yes
Self-Employed Group	Entr.	Hawkers	Farmers	Hawkers
Comparison Group	Salaried	Salaried	Salaried	Other Entr.
Nobs	866,453	449,597	666,029	476,370
Adjusted R-squared	0.678	0.690	0.599	0.655

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Economic Channels

- Where are the effects stronger?
  - Occupation
  - Regions
- Does it affect borrowing?
  - Quantity

Stronger Effects in Financially Less Developed Regions

Table: Effects Across Financial Development

Lower Fin Dev: 1-Percentile Ranking Based on Bank Branch/Population			
	(1)	(2)	(3)
	Income	Bus(Y/N)	Bus Inc
Lagged Cashless Payment	0.061***	0.005	0.085
	(0.012)	(0.006)	(0.061)
Lagged Cashless Payment x Lower Fin Dev	0.033***	0.016***	0.177***
	(0.007)	(0.003)	(0.038)
Household Fixed Effects	Yes	Yes	Yes
Year-Qtr Fixed Effects	Yes	Yes	Yes
Urban x Year-Qtr Fixed Effects	Yes	Yes	Yes
Sample	All	All	All
Nobs	2,156,732	2,156,732	2,156,732
Adjusted R-squared	0.557	0.502	0.513

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Borrowing Constraints

Table: Borrowings and Cashless Payments

Dependent Variables: (1) Borrowings for business; (2) Bank Borrowing; (3) Informal Borrowing

	(1) Business	(2) Formal	(3) Informal
Lagged Cashless Payments	0.0122***	0.0144**	-0.0312**
	(0.0034)	(0.0064)	(0.0148)
Household Fixed Effects	Yes	Yes	Yes
Year-Qtr Fixed Effects	Yes	Yes	Yes
Urban x Year-Qtr Fixed Effects	Yes	Yes	Yes
Nobs	1,433,159	1,433,159	1,433,159
Adjusted R-squared	0.369	0.302	0.324

standard error in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Hawkers' Borrowing Constraints

- Change in composition of borrowing from informal to formal sources

Table: Borrowings and Cashless Payments Across Occupation

Dependent Variables: (1) Borrowings for business; (2) Bank Borrowing; (3) Informal Borrowing

	(1) Business	(2) Formal	(3) Informal
Hawkers X Lagged Cashless Payments	0.0005	0.0078***	-0.0061**
	(0.0018)	(0.0019)	(0.0029)
Household Fixed Effects	Yes	Yes	Yes
District x Year-Qtr Fixed Effects	Yes	Yes	Yes
Nobs	306,818	306,818	306,818
Adjusted R-squared	0.452	0.389	0.473

standard error in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

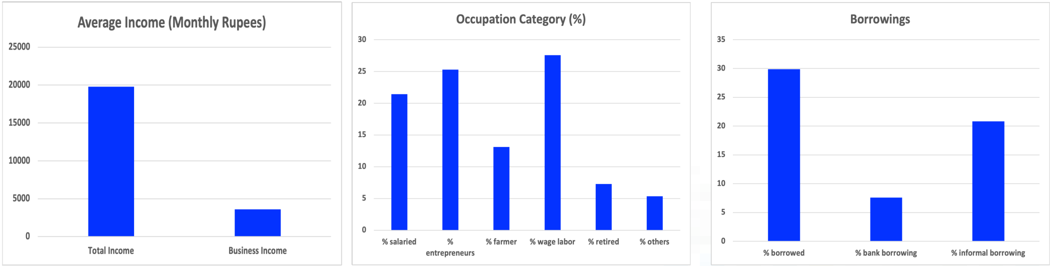
Alternatives

- Are results drive by simply better recording of income? Problems with survey data?
    - Night-light data (WIP) nightlight
    - Consumption data durable
    - RBI data on bank credit in a district-quarter RBI
- Are results driven by other financial inclusion programs (e.g., PMJDY)?
    - District-level variation in the fraction of PMJDY account. pmjdysum . pmjdyreg
    - Bank level variation in the fraction of PMJDY account. pmjdybank
- How generalizable are the results beyond a setting of demonetization shock?
    - Results persistent over time
    - Within-occupation variation unlikely driven by the direct effect of demonetization
    - External validity beyond India?

Conclusion

- Digital payments can positively affect real economy.
- Marginal businesses more likely to benefit.
- Financially less developed areas more likely to benefit.
- Quantity of credit goes up.

Key Descriptive Statistics



(a) Income (b) Nature of Occupation (c) Borrowings

▸ Back

Descriptive Statistics of Key Variables

	Mean	SD	P25	P50	P75	N
Cashless Transaction (bil.)	15.21	52.80	0.76	2.63	9.09	2,361,213
Cashless Transaction/Person	3378.58	4915.96	1041.60	1833.04	3507.12	2,361,213
Monthly Income	19780.55	16061.60	9400.00	15000.00	24666.67	4,985,092
Monthly Business Income	3605.90	10283.76	0.00	0.00	0.00	4,985,092
% with business income	16.55	37.16	0.00	0.00	0.00	4,985,092
% with borrowing	29.90	45.78	0.00	0.00	100.00	3,583,735
% borrowing for business	3.50	18.38	0.00	0.00	0.00	3,583,735
% with bank borrowing	7.59	26.49	0.00	0.00	0.00	3,583,735
% with borrowing NBFC	1.68	12.84	0.00	0.00	0.00	3,583,735
% with borrowing informal	20.82	40.60	0.00	0.00	0.00	3,583,735
% entrepreneur	25.28	43.46	0.00	0.00	100.00	4,985,092
% hawkers	3.29	17.83	0.00	0.00	0.00	4,985,092
% farmers	13.10	33.74	0.00	0.00	0.00	4,985,092
% salaried	21.32	40.95	0.00	0.00	0.00	4,985,092

Back

Lead Bank Presence

Table: Presence of Lead Bank in a District

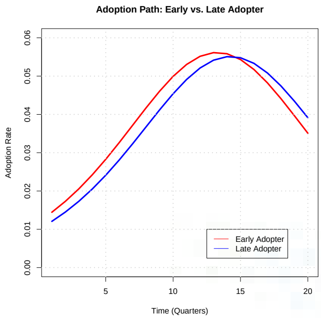
Number of Lead Banks in a District

	(1)	(2)	(3)	(4)
	Branches	Branches	Log(Branches)	Log(1+Branches)
main				
Lead Bank	31.4379***	2.1589***	2.2966***	2.6288***
	(1.1688)	(0.0376)	(0.0235)	(0.0238)
District Fixed Effects	Yes	Yes	Yes	Yes
Nobs	21,042	21,042	12,877	21,042
Adjusted R-squared	0.3527		0.3162	0.3394
Number of Districts	501		501	501
Model	OLS	Poisson	OLS	OLS

standard error in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Back

Tech Adoption: Initial Condition



- Diffusive model of adoption (Bass, 1969):

$$\frac{f(t)}{1 - F(t)} = p + q \times F(t)$$

- Model calibrated to: q=0.2, and p=0.012 for early adopter, p=0.010 for late.

IV Estimates

Table: Early vs. Late Adopters: 2SLS Regression

Outcome Across Early & Late Districts	(1) Cashless Payment	(2) Income	(3) Owns Business	(4) Business Income
Early x Post	0.3243***			
	(0.0400)			
Digital Payments		0.2763***	0.0455**	0.5451***
		(0.0637)	(0.0194)	(0.1963)
Household FE	Yes	Yes	Yes	Yes
State x Year-Quarter FE	Yes	Yes	Yes	Yes
Urban x Year-Quarter FE	Yes	Yes	Yes	Yes
Demon. x Year-Quarter FE	Yes	Yes	Yes	Yes
Nobs	748,641	748,641	748,641	748,641
Adjusted R-squared	0.987	.	.	.

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Purchase of Durable Goods

$$y_{idt} = h_i + yq_t + u_i \times yq_t + \beta \times log(digital)_{d,t-1} + \epsilon_{idt}$$

Table: Asset Purchase

	(1) Generator	(2) Car	(3) Television	(4) Air-Cond.	(5) Computer
Lagged Cashless Payments	0.0025**	0.0018**	0.0016	0.0025***	0.0037***
	(0.0011)	(0.0007)	(0.0028)	(0.0007)	(0.0008)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Urban x Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Nobs	1,433,159	1,433,159	1,433,159	1,433,159	1,433,159
Adjusted R-squared	0.033	0.045	0.056	0.019	0.042

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Back

Table: Cashless Payments and Night Lights

Dep Var: log(Quarterly Night Light Intensity), district-quarter level regression

	(1) Night Light	(2) Night Light	(3) Night Light	(4) Night Light
Lagged Cashless Payments	0.0307***	0.0321***	0.0419***	0.0305***
	(0.0086)	(0.0106)	(0.0106)	(0.0098)
District Fixed Effects	Yes	Yes	Yes	Yes
Year-Qtr Fixed Effects	Yes	Yes	Yes	Yes
Demonetization x Year-Qtr Fixed Effects	No	Yes	Yes	Yes
State x Year-Qtr Fixed Effects	No	No	Yes	Yes
FinDev x Year-Qtr Fixed Effects	No	No	No	Yes
Literacy x Year-Qtr Fixed Effects	No	No	No	Yes
Population x Year-Qtr Fixed Effects	No	No	No	Yes
Nobs	7,792	6,912	6,912	6,912
Adjusted R-squared	0.952	0.950	0.973	0.974

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Back

Table: Cashless Payments and RBI Credit: Panel Data

Dep Var: log(Quarterly RBI Credit)

	(1)	(2)	(3)	(4)	(5)
Cashless Payment.L1	0.0243***				0.0316***
	(0.0086)				(0.0059)
Cashless Payment.L2		0.0233***			-0.0100***
		(0.0083)			(0.0030)
Cashless Payment.L3			0.0233***		0.0024
			(0.0085)		(0.0031)
Cashless Payment.L4				0.0220***	0.0156***
				(0.0082)	(0.0060)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Nobs	8,064	7,560	7,056	6,552	6,552
Adjusted R-squared	0.9976	0.9977	0.9979	0.9980	0.9981
Number of Districts	504	504	504	504	504
p-value (F-test)					0.0005

standard error in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Bank Accounts Across Early vs. Late Banks

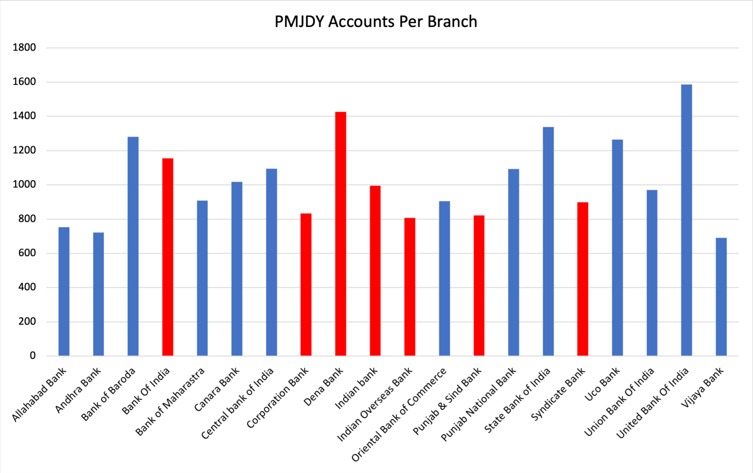


Figure: Early (Blue) vs. Late (Red)

PMJDY Account Opened Across Early vs. Late Banks

Table: Summary Statistics: PMJDY Accounts

Data from Maharashtra and Tamilnadu, accounts opened by 2022

Panel A: All Districts in MH & TN

	Mean	SD	Min	P50	Max	N
Per Capita Accounts	0.233	0.089	0.072	0.243	0.482	31
log (no. of accounts)	13.294	0.589	12.336	13.214	14.353	31
Panel B: Late Districts						
Per Capita Accounts	0.225	0.099	0.072	0.234	0.482	17
log (no. of accounts)	13.173	0.527	12.336	13.171	14.263	17
Panel C: Early Districts						
Per Capita Accounts	0.243	0.076	0.130	0.267	0.366	14
log (no. of accounts)	13.441	0.646	12.371	13.522	14.353	14

Back

DD Results with control for PMJDY Accounts

Table: Cashless Payments and Outcomes: Controlling for PMJDY Accounts

Data from Maharashtra and Tamilnadu

	(1) Income	(2) Bus(Y/N)	(3) Bus Inc	(4) Entr(Y/N)	(5) Income
Early x Post	0.0962***	0.0374***	0.4039***	0.0504***	0.1033***
	(0.0211)	(0.0060)	(0.0633)	(0.0052)	(0.0216)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
State x Yr-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Urban x Yr-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demonetization x Yr-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
PMJDY x Year-Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sample	MH+TN	MH+TN	MH+TN	MH+TN	MH+TN
Nobs	431,137	431,137	431,137	431,137	84,124
Adjusted R-squared	0.511	0.327	0.347	0.382	0.661

standard error in parentheses
$^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$