Shocks and Technology Adoption: Evidence from Electronic Payment Systems

Nicolas Crouzet, Apoorv Gupta & Filippo Mezzanotti

Kellogg and Dartmouth
Motivation

Many Fintech products are network technologies peer-to-peer lending; electronic payment platforms

Decisions to adopt are complements across users [Katz and Shapiro 1986, Farrell and Saloner 1986] coordination problems theoretical possibility, but quantitative importance?

This paper: evidence on coordination problems

network technology: electronic wallet

empirical setting: Indian demonetization of 2016
Results

① Model: Large but temporary shock \(\Rightarrow\)

- P1 Persistent increase in network size
- P2 Persistent increase in network growth rate
- P3 State-dependence w.r.t. initial network size

② Reduced-form tests

Instrument: geographic variation in exposure to demonetization
Adoption response consistent with P1-P3

③ Structural estimation

6-month adoption response 60% smaller w/o externalities
Trade-off btw. shock persistence and dispersion of adoption
Related literature

Dynamic coordination problems


  this paper: test predictions on persistence and state dependence

Payments in Fintech

- Higgins (2019)

  this paper: coordination is an obstacle even if $\approx 0$ adoption costs

Indian demonetization of 2016

- Chodorow-Reich et al. (2018)

  this paper: imperfect substitutability btw. cash and e-money
Plan

1. Background

2. Theory

3. Reduced-form evidence

4. Structural estimation + counterfactuals
1. Background
The Indian demonetization of 2016

Nov 2016: surprise announcement

Existing Rs.500 and Rs.1000 notes voided
Swap to new Rs.500 and Rs.2000 notes

Nov 2016 - Jan 2017: cash crunch

Gov’t withdrawal limits
Logistical problems in currency distribution

After Jan 2017: cash shortage abates

Withdrawal limits lifted
Growth of currency in circulation resumes
The Indian demonetization of 2016

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% monthly change

Currency in circulation
Currency in circulation + Deposits

Months after shock

Cash queries
Payments adoption during the Demonetization

Study a large provider of electronic wallets
registration only requires bank account + mobile phone
no set-up fees, no transaction fees

Sample

≈ 1 million firms
amount and # of transactions; geo identifiers
weekly (May 2016 to June 2017)
Debit and credit cards
2. Model
Model description (1/2)

Flow profits for firm $i \in [0, 1]$: 

$$
\Pi(x_{i,t}, M_t, X_t) = \begin{cases} 
M_t & \text{if } x_{i,t} = c \\
M^e + CX_t & \text{if } x_{i,t} = e
\end{cases} \quad \text{(cash)}
$$

Aggregate states $(M_t, X_t)$

$$
dM_t = \theta (M^c - M_t) + \sigma dZ_t \\
X_t = \int 1 \{x_{i,t} = e\} \, di
$$

Firm $i$ can switch $c \leftrightarrow e$ at Poisson rate $\tilde{k} \in [0, k]$
Model description (2/2)

Optimal switching rate:

$$a_t(M_t, X_t) = 1 \left\{ \mathbb{E}_t \left[ \int_{s \geq 0} e^{-(r+k)s} \Delta \Pi(M_{t+s}, X_{t+s}) ds \right] \geq 0 \right\}$$

$$\tilde{k}_t(x_{i,t}, M_t, X_t) = \begin{cases} 
ka_t(M_t, X_t) & \text{if } x_{i,t} = c \\
(1 - a_t(M_t, X_t))k & \text{if } x_{i,t} = e 
\end{cases}$$

Law of motion for $X_t$:

$$dX_t = (1 - X_t)a_t k dt - X_t(1 - a_t) k dt$$

$$= (a_t - X_t) k dt$$

$C > 0 \rightarrow$ adoption complementarities: $a_t(M_t, X_t)$
No adoption complementarities \((C = 0)\)
Phase diagram

$\Phi_t(X_t)$

$dX_t > 0$

$dX_t < 0$

Stationary distribution of $X_t$

No adoption complementarities ($C = 0$)
Phase diagram

Stationary distribution of $X_t$

No adoption complementarities ($C = 0$)
No adoption complementarities ($C = 0$)
Phase diagram

\[ dX_t < 0 \]

\[ dX_t > 0 \]

Stationary distribution of \( X_t \)

No adoption complementarities \( (C = 0) \)
Phase diagram

$\Phi_t(X_t)$

$M_t$

$M_0$

$dX_t > 0$

$dX_t < 0$

Stationary distribution of $X_t$

No adoption complementarities $(C = 0)$
No adoption complementarities ($C = 0$)
Phase diagram

Stationary distribution of $X_t$

Adoption complementarities ($C > 0$)
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Adoption complementarities $(C > 0)$
Adoption complementarities ($C > 0$)
Phase diagram

- $dX_t < 0$
- $dX_t > 0$

Stationary distribution of $X_t$

Adoption complementarities ($C > 0$)
Phase diagram

$dX_t < 0$

$dX_t > 0$

$\Phi_t(X_t)$

$M_t$

$M^c$}

Stationary distribution of $X_t$

Adoption complementarities ($C > 0$)
The response of adoption to large shocks

Characterize impulse responses

\[ I_X(t; M_0, X_0) = \mathbb{E}_0 [X_t \mid M_0, X_0] \]
\[ I_a(t; M_0, X_0) = \mathbb{E}_0 [a_t \mid M_0, X_0] \]

up to horizon

\[ t > \theta^{-1} \log(2) = \text{shock half-life} \]
Prediction 1: \( C > 0 \implies \) persistent increase in user base \( (X_t) \)

Numerical result: The IRF of the user base \( X_t \) is increasing in \( C \):

\[
\frac{\partial}{\partial C} \mathcal{I}_X(t; M_0, 0) \geq 0.
\]
Prediction 2: $C > 0 \implies \text{persistent increase in adoption rate } (a_t)$

Numerical result: The IRF of the adoption rate $a_t$ is increasing in $C$:

$$\frac{\partial}{\partial C} I_a(t; M_0, 0) \geq 0.$$
**Prediction 3:** $C > 0 \implies \text{state-dependence}$

![Graph](image)

**Numerical result:** When $C > 0$, the IRF of the adoption rate $a_t$ increases with $X_0$:

$$\frac{\partial}{\partial X_0} \mathcal{I}_a(t; M_0, X_0) > 0.$$
Prediction 3: \( C > 0 \implies \text{state-dependence} \)

Numerical result: When \( C > 0 \), the IRF of the adoption rate \( a_t \) increases with \( X_0 \):

\[
\frac{\partial}{\partial X_0} \mathcal{I}_a(t; M_0, X_0) > 0.
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Numerical result: When $C > 0$, the IRF of the adoption rate $a_t$ increases with $X_0$:

$$\frac{\partial}{\partial X_0} I_a(t; M_0, X_0) > 0.$$
Summary

When $C > 0$:

**P1** Persistent response of user base $X_t$

**P2** Persistent response of adoption rate $a_t$

**P3** State-dependence with respect to $X_0$

Next: test **P1-P3** using district- and firm-level data
3. Reduced-form evidence
Empirical setting

Limits of aggregate event study

other aggregate shocks after Nov. 2016 (P1, P2)
no variation in initial adoption (P3)

District-level analysis

District-level exposure: market share of chest banks
commercial banks handling cash distribution within districts

\[
\text{Chest share}_d = \frac{\text{Chest bank deposits}_d}{\text{Total bank deposits}_d}
\]

\[
\text{Exposure}_d = 1 - \text{Chest share}_d
\]
Validation of exposure measure

![Graph showing the relationship between Δ Bank Deposits and Exposure]
Main specification

\[
\log (y_{d,t}) = \alpha_t + \alpha_d + \delta_t (\text{Exposure})_d + \Gamma'_t Y_d + \epsilon_{d,t}
\]

d : district

t : month (May 2016 to June 2017)

\(Y_d\) : district covariates (to ensure conditional balance)

s.e. clustered by district

Table

Result excluding individual states  Placebo using consumption survey data
Total firms on the platform (P1)
New firms on the platform (P2)
Testing for state-dependence (P3)

Direct test

Districts with higher $X_0$ (pre-shock user base) respond more

Instrumenting for initial adoption

Stronger effects for districts close to a large electronic payment hub?

$$X_{d,t} = \alpha_t + \alpha_d + \delta_t D_d + \Gamma'_t Y_d + \epsilon_{d,t}$$

$$D_d = \text{min distance to the 5 largest pre-shock hubs}$$
Distance to hub and number of firms (P3)

Effect on # of active firms

Time

-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8
Distance to hub and number of new firms (P3)
Alternative explanations (1/2)

① $C = 0$, but persistent shock and/or slow switching rate (low $\theta +$ low $k$)

By Jan 2017, currency in circulation/GDP back to $> 90\%$ pre-shock level

Model with low $k +$ low $\theta \implies \text{P1 and P2, but not P3}$

② $C = 0$, but fixed costs of switching

For firms in our sample, no purchase of POS terminal required; no sign-up fees

Model with $C = 0$ but fixed cost $\implies \text{P1, but not P2 or P3}$

③ $C = 0$, but demand shock

Higher exposure predicts lower consumption
Alternative explanations (2/2)

4. $C = 0$, but adoption response driven by learning
   - Pre-Nov adopters: persistent increase in activity
   - Nov-Jan adopters: shock exposure predicts increase in activity from Feb to June

   Index of social connectivity does not predict stronger response to shock
   - Survey: 36% "friends and family" vs. 80% "stores started accepting e wallets"

5. $C = 0$, but reflection problem
   - State-dependence \((P3)\) explained by common unobserved component
     - e.g. distance to hub corr. w/ propensity to adopt new products

   Empirically, distance to hub does not predict
   - growth in loans made on fintech platform
   - growth in number of bank deposit accounts
   - growth in number of mobile phones
Summary

Reduced-form evidence qualitatively consistent w/ model predictions when $C > 0$

- **P1** Persistent response of user base
- **P2** Persistent response of adoption rate
- **P3** State-dependence

Quantitative impact of complementarities?
4. Structural estimation and counterfactuals
Estimation

5 structural parameters:

- $C$: Complementarities
- $k$: Max switching rate
- $S$: Shock to cash demand
- $M^e$: Returns to $e$ when $X_t = 0$
- $\sigma$: Volatility of innovations to $M_t$

8 moments from the panel of districts:

\[
\Delta_{t_0} X_{d,t} = \beta + \gamma 1 \{ t \geq t_0 + 3 \} + \delta X_{d,t_0} + \zeta (1 \{ t \geq t_0 + 3 \} \times X_{d,t_0}) + \epsilon_{d,t},
\]
\[
\var_t(\Delta_{t_0} X_{d,t}) = \eta + \kappa 1 \{ t \geq t_0 + 3 \} + \mu_t,
\]
\[
\var_d(\Delta_{t_0} X_{d,t}) = \nu + \omega_d,
\]

along with $\hat{\epsilon}^2_{d,t} = \xi + \omega_{d,t}$. 

Estimation

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Estimation

5 structural parameters:

- $C$: Complementarities $\rightarrow \gamma$
- $k$: Max switching rate
- $S$: Shock to cash demand
- $M^e$: Returns to $e$ when $X_t = 0$
- $\sigma$: Volatility of innovations to $M_t$

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\[ \hat{\var}_d(\Delta_{t_0} X_{d,t}) = \nu + \omega_d, \]

along with $\hat{\epsilon}^2_{d,t} = \xi + \omega_{d,t}$. 

Estimation

5 structural parameters:

- $C$: Complementarities $\rightarrow \gamma$
- $k$: Max switching rate $\rightarrow \kappa$
- $S$: Shock to cash demand $\rightarrow \beta$
- $M^e$: Returns to $e$ when $X^t = 0$ $\rightarrow \nu$
- $\sigma$: Volatility of innovations to $M^t$ $\rightarrow \xi$

8 moments from the panel of districts:

\[
\Delta_{t_0}X_{d,t} = \beta + \gamma 1 \{ t \geq t_0 + 3 \} + \delta X_{d,t_0} + \zeta \left( 1 \{ t \geq t_0 + 3 \} \times X_{d,t_0} \right) + \epsilon_{d,t},
\]
\[
\hat{\text{var}}_t(\Delta_{t_0}X_{d,t}) = \eta + \kappa 1 \{ t \geq t_0 + 3 \} + \mu_t,
\]
\[
\hat{\text{var}}_d(\Delta_{t_0}X_{d,t}) = \nu + \omega_d,
\]
along with $\hat{\epsilon}^2_{d,t} = \xi + \omega_{d,t}$. 
Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>C Complementarities</td>
<td>0.063</td>
<td>(0.004)</td>
</tr>
<tr>
<td>k Max switching rate</td>
<td>0.163</td>
<td>(0.041)</td>
</tr>
<tr>
<td>S Shock to cash demand</td>
<td>0.246</td>
<td>(0.047)</td>
</tr>
<tr>
<td>M Returns to e when X = 0</td>
<td>0.970</td>
<td>(0.004)</td>
</tr>
<tr>
<td>σ Volatility of innovations to Mt</td>
<td>0.039</td>
<td>(0.011)</td>
</tr>
</tbody>
</table>

- Reject null of $C = 0$

3.0% lower profits if $X = 0$, 3.3% higher if $X = 1$

- Short-run decline in cash-based revenue: 24.6% or 6 s.d.

3× of G.E. estimates of Chodorow-Reich et al. (2020)
Average change in adoption relative to October 2016 \( (E_{t_0} [\Delta_{t_0} X_{d,t}]) \)

Data
Baseline
Counterfactual: no complementarities

(month-end)

0
1
2
3
4
5
6
7
8
%

Average change in adoption relative to October 2016 \( (E_{t_0} [\Delta_{t_0} X_{d,t}]) \)
## Counterfactuals

Short-lived shocks $\implies$ state-dependence $\implies$ more dispersion

\[
\arg\max_{S, \theta} \quad \mathbb{E}_{t_0} \left[ \Delta_{t_0} X_{d, t_0+T} \right] - \frac{g}{2} \text{var}_{t_0} \left[ \Delta_{t_0} X_{d, t_0+T} \right] \quad \text{s.t.} \quad B(S, \theta) \leq B(\hat{S}, \theta_0)
\]

\[
B(S, \theta) = \text{NPV of } M^c - M_t
\]

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Alternative policy interventions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$g = 0$</td>
</tr>
<tr>
<td>Shock size (p.p.)</td>
<td>24.6</td>
<td>21.0</td>
</tr>
<tr>
<td>Shock HL (months)</td>
<td>0.8</td>
<td>1.1</td>
</tr>
<tr>
<td>$\mathbb{E} [\Delta X_d]$ (p.p.)</td>
<td>7.2</td>
<td>8.3</td>
</tr>
<tr>
<td>$sd [\Delta X_d]$ (p.p.)</td>
<td>26.4</td>
<td>36.7</td>
</tr>
</tbody>
</table>
5. Conclusion
Conclusion

Do network externalities play a significant role in the diffusion of Fintech?

In our setting, they account for 60% of adoption response to demonetization.

Implications for policy

large but temporary interventions can be enough to spur adoption

but temporary intervention also exacerbate initial adoption differences
Appendix
Equilibrium characterization

Equilibrium: adoption rules \( \{a_t(M_t, X_t)\} \) that are individual best responses to all other firms following the same adoption rules.

**Result:** Let \( T < +\infty \) and assume that:

\[
\theta_t = \begin{cases} 
\theta & \text{if } t \leq T, \\
0 & \text{if } t > T.
\end{cases}
\]

Then the equilibrium exists and is unique. There exists a function \( \Phi_t(X_t) \) such that:

\[
a_t(M_t, X_t) = 1 \iff M_t \leq \Phi_t(X_t).
\]

If \( C = 0 \), \( \Phi_t(X_t) = \Phi_t \forall X_t \), whereas if \( C > 0 \), \( \Phi_t(X_t) \) is strictly increasing.
Google queries about cash in circulation

- **2000 Rs**
- **ATM Line**
- **ATM Cash Withdrawal Limit Today**
- **Cash**
- **ATM Near Me With Cash**
- **Authority Letter for Cash Deposit**
Microfoundations: two-sided market and multi-homing (1/3)

Consumers allocate deposits to cash $L^c_t$ and the electronic wallet $L^e_t$ subject to:

$$\max_{C^c_t, C^e_t, L^c_t, L^e_t} X_t (\zeta C^e_t + (1 - \zeta)C^c_t) + (1 - X_t)C^c_t - \frac{1}{2\gamma} (L^e_t - L^e)^2$$

s.t. $L^c_t + L^e_t \leq D \ [\lambda_t]$

$\quad L^c_t \leq L_t \ [\mu_t]$  

$\quad C^c_t \leq L^c_t \ [\nu^c_t]$  

$\quad C^e_t \leq L^e_t \ [\nu^e_t]$  

$X_t$ is the fraction of firms that accept both the wallet, and cash.

If matched with a firm that accepts both (prob. $X_t$), choose the wallet w.p. $\zeta$. 


Firm profits are given by:

\[
\Pi(x_{i,t}, C_t^c, C_t^e) = \begin{cases} 
\zeta C_t^e + (1 - \zeta)C_t^c & \text{if } x_{i,t} = e, \\
C_t^e & \text{if } x_{i,t} = c.
\end{cases}
\]

e now denotes a firm that accepts both electronic money and cash.
Assume that $D \geq L_t + L^e + \gamma \zeta$. With $L^e_t = C^e_t$, $L^c_t = C^c_t$, we have:

$$C^c_t + C^e_t < D$$

$$C^e_t = L^e + \gamma \zeta X_t$$

$$C^c_t = L_t$$

Therefore:

$$\Delta \Pi(X_t, L_t) = \zeta (L^e + \gamma \zeta X_t - L_t)$$

which is isomorphic to the baseline model, with, in particular:

$$C = \gamma \zeta^2.$$
Estimation methodology: SMM

Objective function:

$$\hat{\Theta} = \arg \min \left( \hat{\Xi} - \frac{1}{S} \sum_{s=1}^{S} \Xi_{\text{sim}}(\Theta; \gamma_s) \right)' \left( \hat{\Xi} - \frac{1}{S} \sum_{s=1}^{S} \Xi_{\text{sim}}(\Theta; \gamma_s) \right),$$

where $\hat{\Xi} = (\hat{\beta}, \hat{\gamma}, \hat{\delta}, \hat{\zeta}, \hat{\xi}, \hat{\eta}, \hat{\kappa}, \hat{\nu})$.

Use the optimal weighting matrix:

$$W = \frac{1}{N_m} \text{var} \left( \hat{\Xi} \right)^{-1},$$

with $\text{var} \left( \hat{\Xi} \right)$ estimated using the bootstrap, clustering by district:

$$\text{var} \left( \hat{\Xi} \right) = \frac{1}{B - 1} \sum_{b=1}^{B} (\hat{\Xi}_b - \hat{\Xi})' (\hat{\Xi}_b - \hat{\Xi}).$$
**Validation of exposure measure: table**

<table>
<thead>
<tr>
<th></th>
<th>Δ log(deposits)</th>
<th>Δ log(deposits\textsuperscript{adj.})</th>
<th>Δ log(deposits\textsuperscript{N})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Chest Exposure</td>
<td>0.094***</td>
<td>0.083***</td>
<td>0.085***</td>
</tr>
<tr>
<td></td>
<td>[0.013]</td>
<td>[0.012]</td>
<td>[0.013]</td>
</tr>
<tr>
<td>log(Pre Deposits)</td>
<td>-0.035***</td>
<td>-0.035***</td>
<td>-0.035***</td>
</tr>
<tr>
<td></td>
<td>[0.003]</td>
<td>[0.003]</td>
<td>[0.063]</td>
</tr>
<tr>
<td>% villages with ATM</td>
<td>0.023</td>
<td>0.020</td>
<td>0.445</td>
</tr>
<tr>
<td></td>
<td>[0.040]</td>
<td>[0.042]</td>
<td>[0.769]</td>
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<tr>
<td>% villages with banks</td>
<td>-0.051**</td>
<td>-0.051**</td>
<td>-1.000**</td>
</tr>
<tr>
<td></td>
<td>[0.023]</td>
<td>[0.024]</td>
<td>[0.449]</td>
</tr>
<tr>
<td>Rural Pop./Total Pop.</td>
<td>-0.063***</td>
<td>-0.070***</td>
<td>-1.224***</td>
</tr>
<tr>
<td></td>
<td>[0.016]</td>
<td>[0.017]</td>
<td>[0.317]</td>
</tr>
<tr>
<td>log(population)</td>
<td>0.036***</td>
<td>0.035***</td>
<td>0.707***</td>
</tr>
<tr>
<td></td>
<td>[0.003]</td>
<td>[0.003]</td>
<td>[0.068]</td>
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<td>Observations</td>
<td>512</td>
<td>512</td>
<td>512</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.118</td>
<td>0.313</td>
<td>0.099</td>
</tr>
<tr>
<td>District Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

**Notes:** Standard errors clustered at district level are reported in brackets. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.
## Validation of exposure measure: placebo

<table>
<thead>
<tr>
<th>Exposure $d$</th>
<th>(1) 2016q4</th>
<th>(2) 2016q3</th>
<th>(3) 2016q2</th>
<th>(4) 2016q1</th>
<th>(5) 2015q4</th>
<th>(6) 2015q3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.621***</td>
<td>-0.404</td>
<td>0.476**</td>
<td>0.137</td>
<td>0.163</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>[0.238]</td>
<td>[0.260]</td>
<td>[0.236]</td>
<td>[0.234]</td>
<td>[0.268]</td>
<td>[0.255]</td>
</tr>
<tr>
<td>Observations</td>
<td>512</td>
<td>512</td>
<td>512</td>
<td>512</td>
<td>512</td>
<td>512</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.313</td>
<td>0.027</td>
<td>0.026</td>
<td>0.162</td>
<td>0.020</td>
<td>0.054</td>
</tr>
<tr>
<td>District Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exposure $d$</th>
<th>(7) 2015q2</th>
<th>(8) 2015q1</th>
<th>(9) 2014q4</th>
<th>(10) 2014q3</th>
<th>(11) 2014q2</th>
<th>(12) 2014q1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.040</td>
<td>0.315</td>
<td>0.345</td>
<td>-0.734***</td>
<td>0.165</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>[0.231]</td>
<td>[0.240]</td>
<td>[0.291]</td>
<td>[0.280]</td>
<td>[0.257]</td>
<td>[0.269]</td>
</tr>
<tr>
<td>Observations</td>
<td>512</td>
<td>512</td>
<td>512</td>
<td>512</td>
<td>512</td>
<td>512</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.044</td>
<td>0.061</td>
<td>0.017</td>
<td>0.037</td>
<td>0.100</td>
<td>0.124</td>
</tr>
<tr>
<td>District Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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</tbody>
</table>

**Notes:** Standard errors clustered at district level are reported in brackets. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 
### Balance Analysis

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>mean</th>
<th>univariate OLS</th>
<th>baseline controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>coeff.</td>
<td>R(^2)</td>
</tr>
<tr>
<td>Log(Pre Deposits)</td>
<td>11.083</td>
<td>-1.290***</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.273)</td>
<td></td>
</tr>
<tr>
<td>% villages with ATM</td>
<td>0.036</td>
<td>0.090***</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.023)</td>
<td></td>
</tr>
<tr>
<td># Bank Branches per 1000's</td>
<td>0.047</td>
<td>0.002</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td># Agri Credit Societies per 1000's</td>
<td>0.045</td>
<td>-0.016</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>% villages with banks</td>
<td>0.085</td>
<td>0.131***</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.036)</td>
<td></td>
</tr>
<tr>
<td>Log(Population)</td>
<td>14.376</td>
<td>-0.501**</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.208)</td>
<td></td>
</tr>
<tr>
<td>Literacy rate</td>
<td>0.622</td>
<td>-0.029</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.025)</td>
<td></td>
</tr>
<tr>
<td>Sex Ratio</td>
<td>0.946</td>
<td>0.008</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>Growth Rate</td>
<td>0.208</td>
<td>-0.219</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.139)</td>
<td></td>
</tr>
<tr>
<td>Working Pop./Total Pop.</td>
<td>0.410</td>
<td>0.026</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>Distance to State Capital(kms.)</td>
<td>0.215</td>
<td>0.035</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>Rural Pop./Total Pop.</td>
<td>0.746</td>
<td>0.170***</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.047)</td>
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</tr>
</tbody>
</table>
## State dependence: within district

<table>
<thead>
<tr>
<th></th>
<th>Log(# transactions)</th>
<th>Log(amount)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>(1(t ≥ t_0) \times 1(\text{Any adopter}_d))</td>
<td>2.803***</td>
<td>4.864***</td>
</tr>
<tr>
<td></td>
<td>(0.246)</td>
<td>(0.346)</td>
</tr>
<tr>
<td>(1(t ≥ t_0) \times \log(\text{Amount of transactions}_d))</td>
<td>0.281***</td>
<td>0.230***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Month f.e.</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>District f.e.</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>District Controls</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>Observations</td>
<td>5,780</td>
<td>5,780</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.609</td>
<td>0.603</td>
</tr>
<tr>
<td>Number of districts</td>
<td>578</td>
<td>578</td>
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</tbody>
</table>

**Notes:** Standard errors clustered at district level are reported in brackets. Significance level: *** \(p < 0.01\), ** \(p < 0.05\), * \(p < 0.1\).
How persistent was the shock?

![Graph showing the effect on total consumption over survey-time. The x-axis represents survey-time from -3 to 3, and the y-axis represents the effect on total consumption from -4 to 4. The data points are shown with error bars indicating variability. A shaded area highlights the period of interest.]
The response of consumption

The figure plots estimates of consumption responses depending on exposure to the shock (Exposure$_d$). The treatment is our measure of Exposure$_d$. The dependent variable on the $y$-axis is the (log) total expense by household. 95% confidence intervals are represented with the vertical lines; standard errors are clustered at the district level.
# Learning: pre-Nov adopters

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
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<tr>
<td></td>
<td>amount</td>
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<td>amount</td>
<td>transactions</td>
<td>transactions</td>
<td>transactions</td>
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<td>transactions</td>
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<td>SR × exposure</td>
<td>1.651***</td>
<td>1.660**</td>
<td>0.721**</td>
<td>0.733**</td>
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<td>[0.339]</td>
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<tr>
<td>LR × exposure</td>
<td>1.276**</td>
<td>1.244*</td>
<td>0.415</td>
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<td>[0.278]</td>
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<tr>
<td>post × exposure</td>
<td>1.370**</td>
<td>1.348**</td>
<td>0.492*</td>
<td>0.486*</td>
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<td>post × exposure × high sci</td>
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<td>post × high sci</td>
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<td>0.579</td>
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<td>SR × exposure × high sci</td>
<td>-1.270</td>
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<td>LR × exposure × high sci</td>
<td>-0.754</td>
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<tr>
<td>Observations</td>
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<td>132,608</td>
<td>132,552</td>
<td>132,552</td>
<td>132,608</td>
<td>132,608</td>
<td>132,552</td>
<td>132,552</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.543</td>
<td>0.544</td>
<td>0.544</td>
<td>0.575</td>
<td>0.575</td>
<td>0.575</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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<td>✓</td>
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</tr>
<tr>
<td>Month f.e.</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>District Controls × Month f.e.</td>
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<td>✓</td>
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</tr>
</tbody>
</table>

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Learning: Nov-Jan adopters

Δ (Transactions_{June 2017}/Transactions_{March 2017}) - 1

Exposure_d

0 0.2 0.4 0.6 0.8

-0.4 -0.2 0 0.2 0.4 0.6 0.8
The reflection problem (1/3)

Effect on loan applications

Month from event
The reflection problem (3/3)

Effect on mobile ownership

Month from event

![Graph showing the effect on mobile ownership over time.](chart.png)
Histogram of exposure
Map of exposure
Results excluding individual states

State excluded from sample

Effect on amount transacted

ANDHRA PRADESH
ASSAM
BHARAT
CHHATTISGARH
GOA
GUJARAT
HARYANA
HIMACHAL PRADESH
JAMMU & KASHMIR
JHARKHAND
KARNATAKA
KERALA
MADHYA PRADESH
MAHARASHTRA
ORISSA
PUNJAB
RAJASTHAN
TAMIL NADU
UTTAR PRADESH
UTTARAKHAND
WEST BENGAL
Placebo using consumption

Effect on Total Consumption

Placebo Survey-time

Traditional electronic payments: intensive margin

Debit Cards (#Trans at ATM)

Debit Cards (Amount at ATM)

Credit Cards (#Trans at Sale Point)

Debit Cards (#Trans at Sale Point)
Traditional electronic payments: extensive margin

# Credit Cards

# Debit Cards