Shocks and Technology Adoption: Evidence from Electronic Payment Systems

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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 $\implies$

   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

- Frankel and Pauzner (2000), Burdzy, Frankel and Pauzner (2001), Guimarães and Machado (2018)

  this paper : test predictions on persistence and state dependence

Payments in Fintech

- Higgins (2019)

  this paper : coordination is an obstacle even if ≈ 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

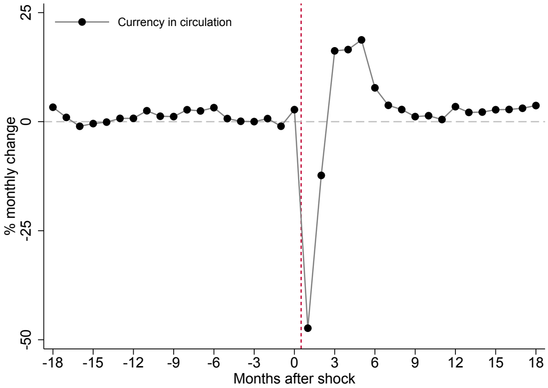
Logistical problems in currency distribution

After Jan 2017: cash shortage abates

Withdrawal limits lifted

Growth of currency in circulation resumes

Cash queries



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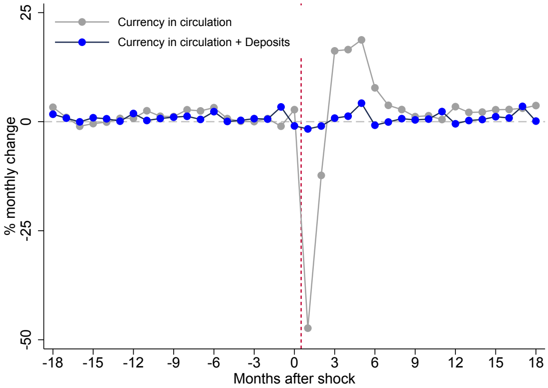


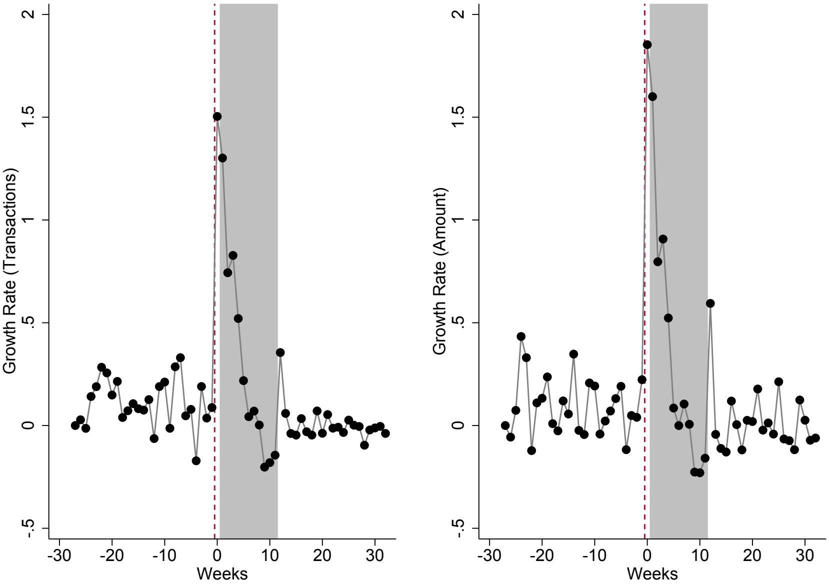
Payments adoption during the Demonetization

Study a large provider of electronic wallets

- registration only requires bank account + mobile phone
- no set-up fees, no transaction fees

Sample

- $\approx$ 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 $i \in [0,1]$:

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

Aggregate states (M_t, X_t)

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

Firm i can switch $c \leftrightarrow e$ at Poisson rate $\tilde{k} \in [0, k]$

Model description (2/2)

Optimal switching rate:

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

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

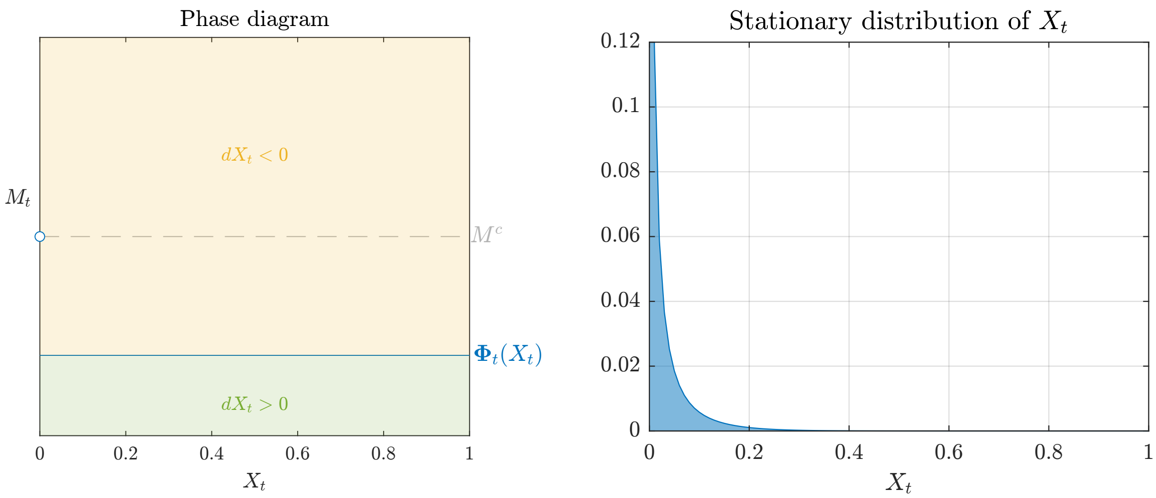
Law of motion for X_t:

Eq'um characterization

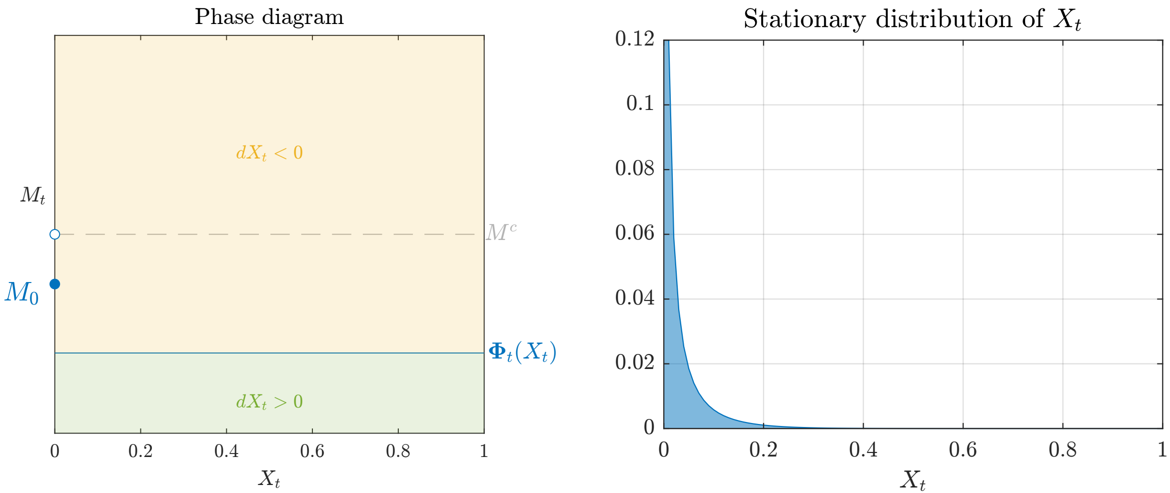
$$\begin{aligned} dX_t &= (1 - X_t)a_t kdt - X_t(1 - a_t)kdt \\ &= (a_t - X_t)kdt \end{aligned}$$

$C > 0 \rightarrow$ adoption complementarities: $a_t(\underset{-}{M_t}, \underset{+}{X_t})$

Two-sided market | Multi-homing



No adoption complementarities ($C = 0$)



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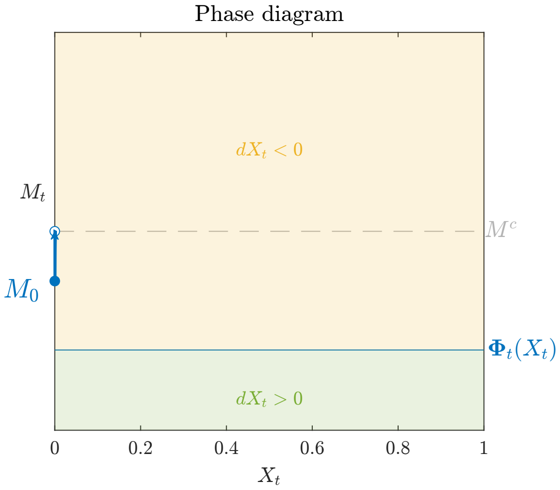

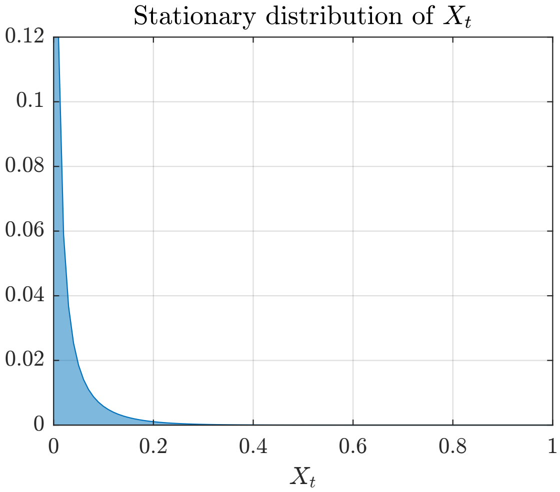

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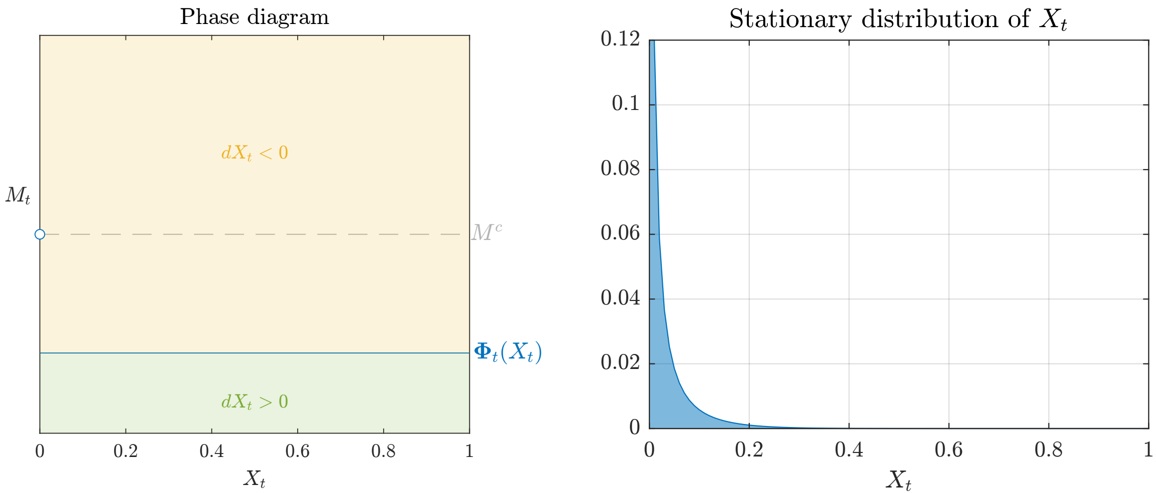

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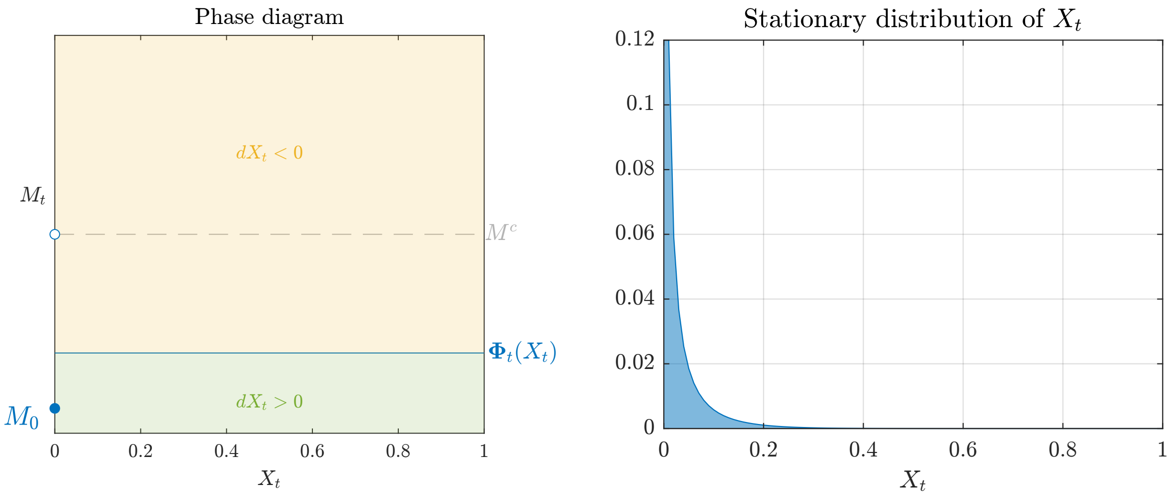

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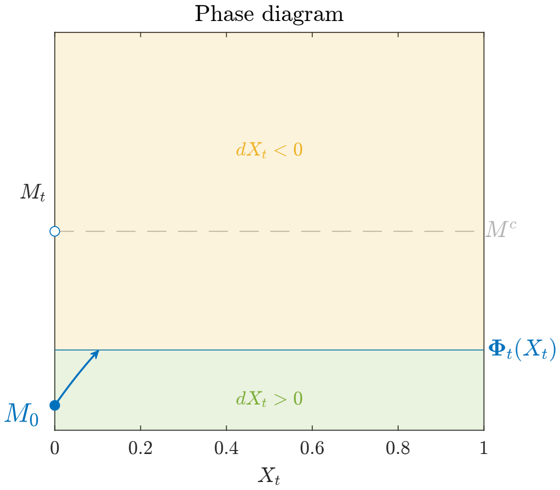

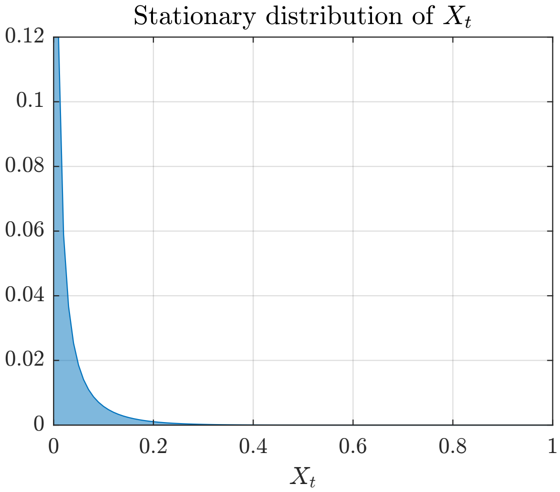

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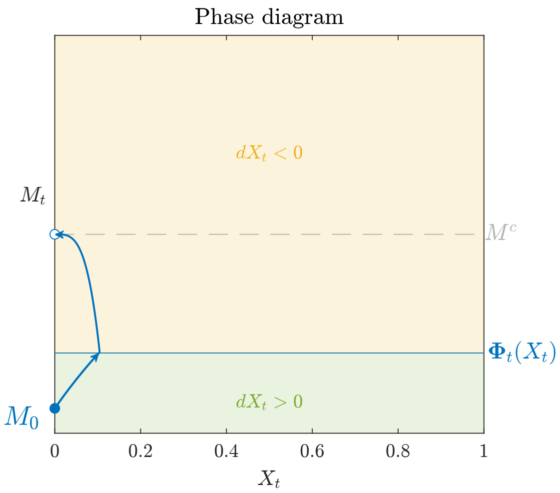

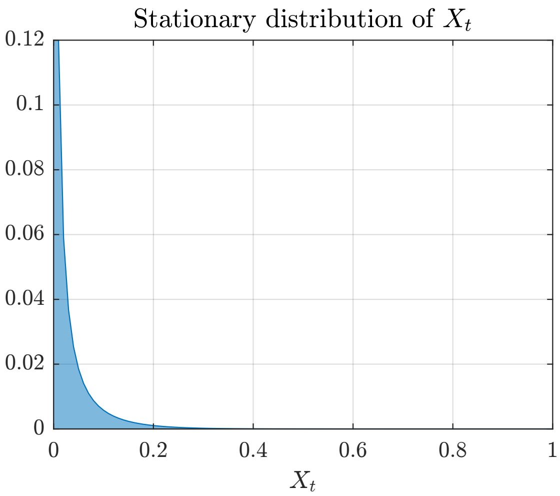

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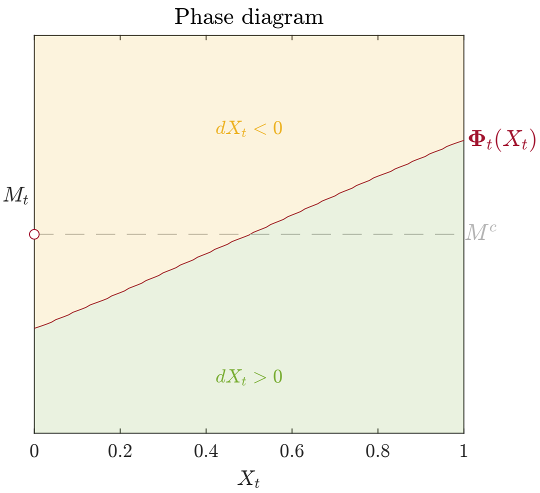
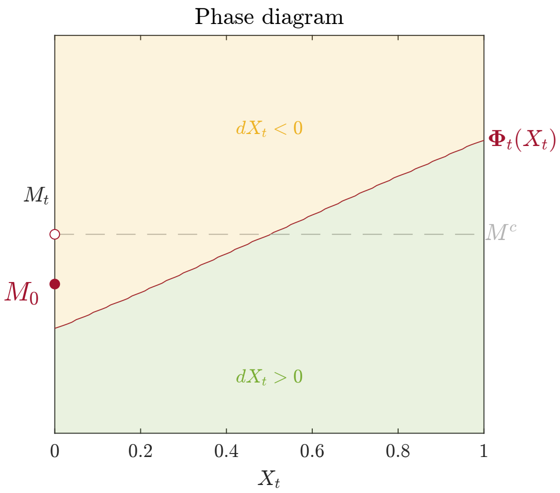


Adoption complementarities ($C > 0$)



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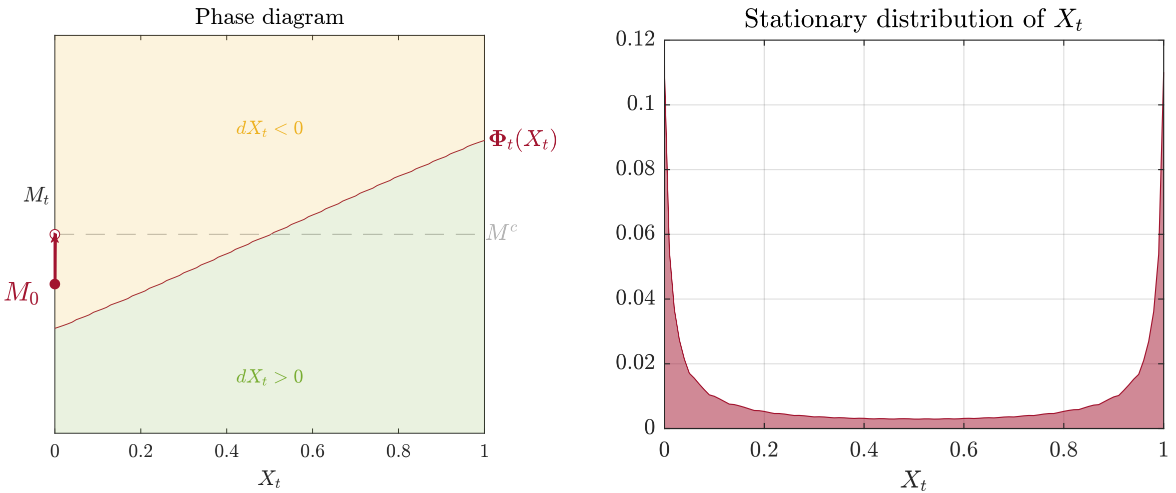

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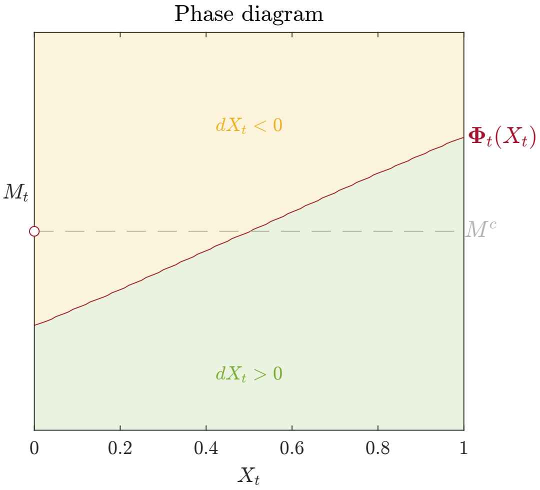

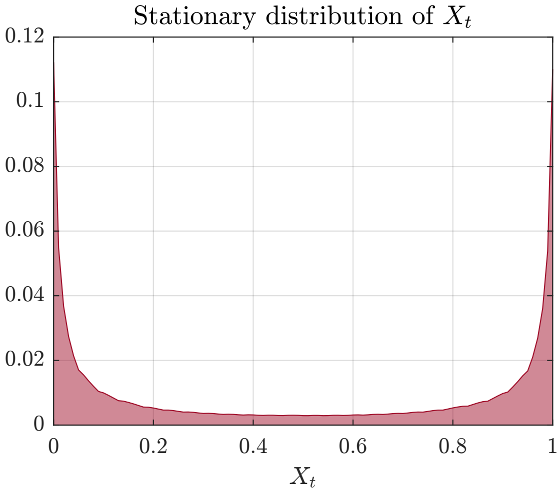

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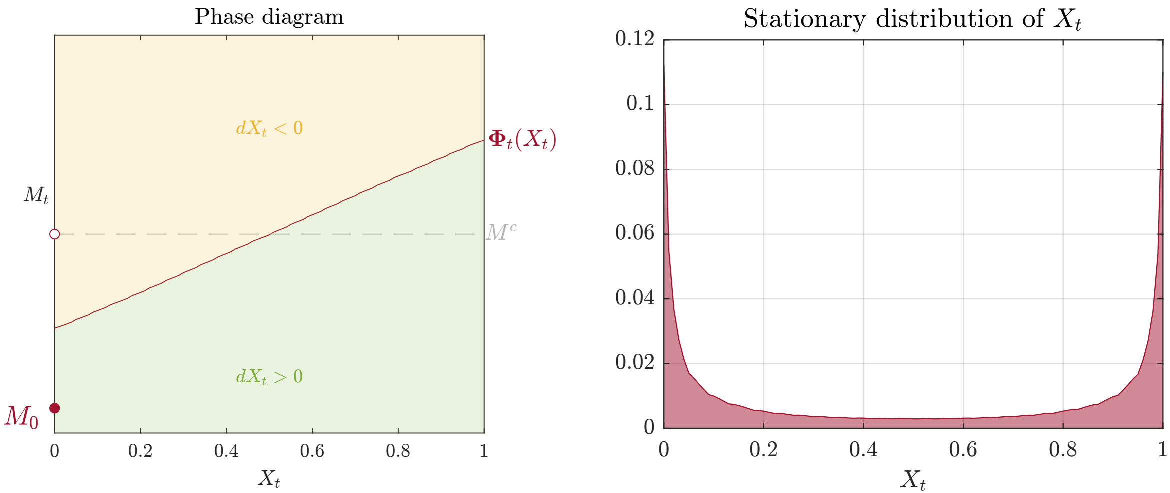

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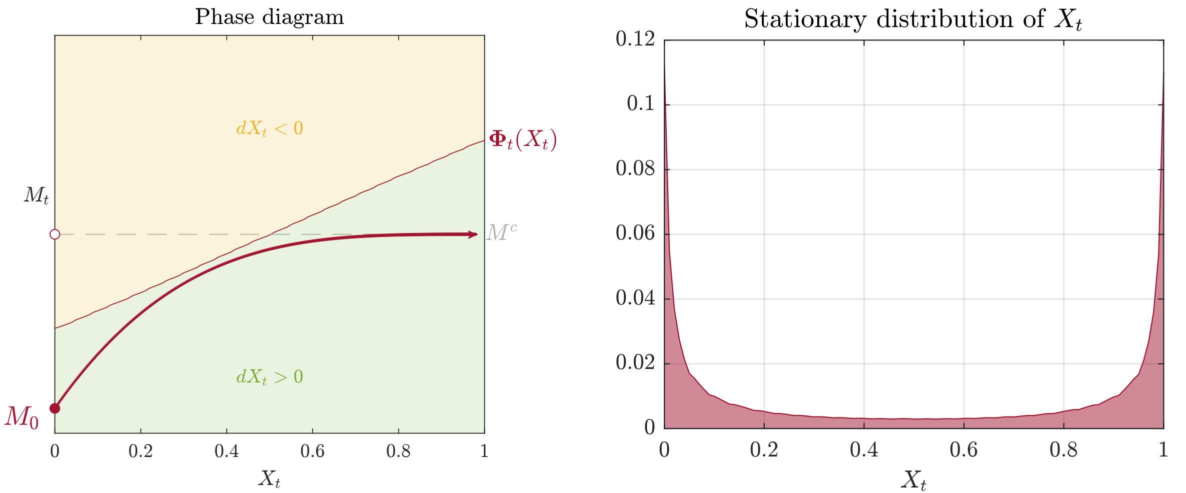
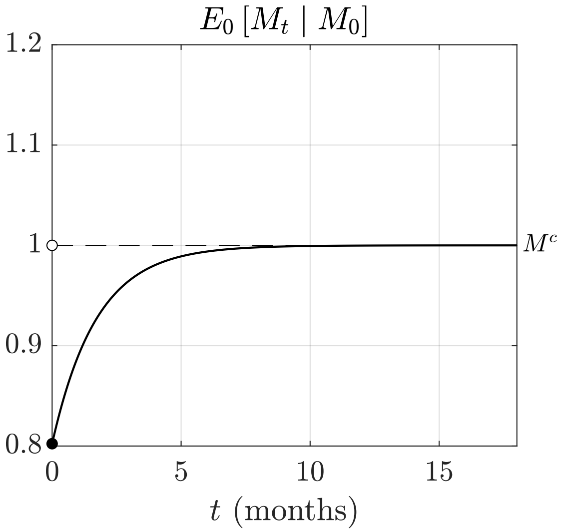


Adoption complementarities ($C > 0$)

The response of adoption to large shocks



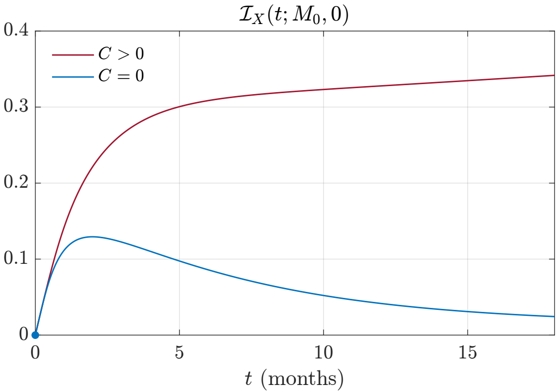
Characterize impulse responses

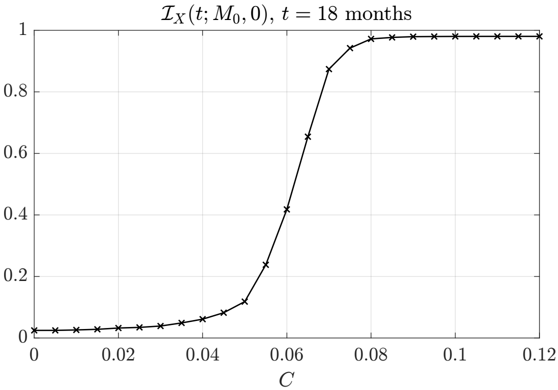
$$\mathcal{I}_X(t; M_0, X_0) = \mathbb{E}_0 [X_t \mid M_0, X_0]$$
$$\mathcal{I}_a(t; M_0, X_0) = \mathbb{E}_0 [a_t \mid M_0, X_0]$$

up to horizon

$$t > \theta^{-1} \log(2) = \text{shock half-life}$$

Prediction 1: $C > 0 \implies$ persistent increase in user base (X_t)

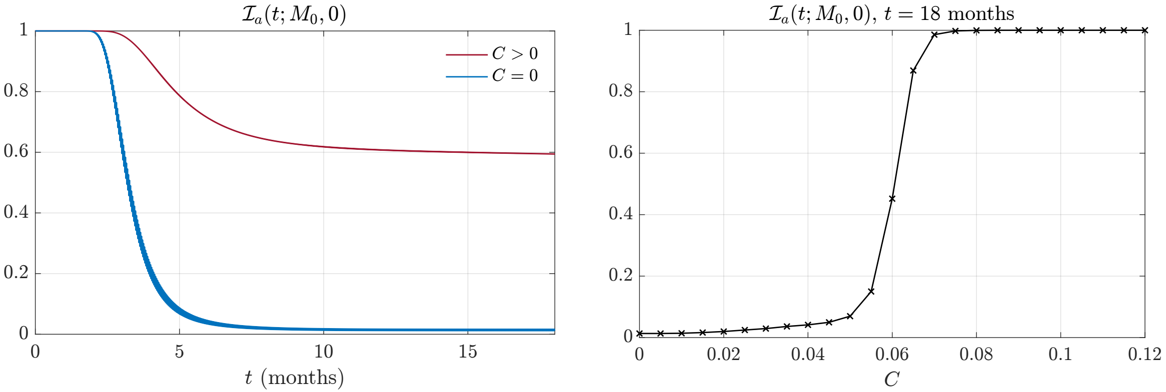




Numerical result: The IRF of the user base X_t is increasing in C:

$$\frac{\partial}{\partial C} \mathcal{I}_X(t; M_0, 0) \geq 0.$$

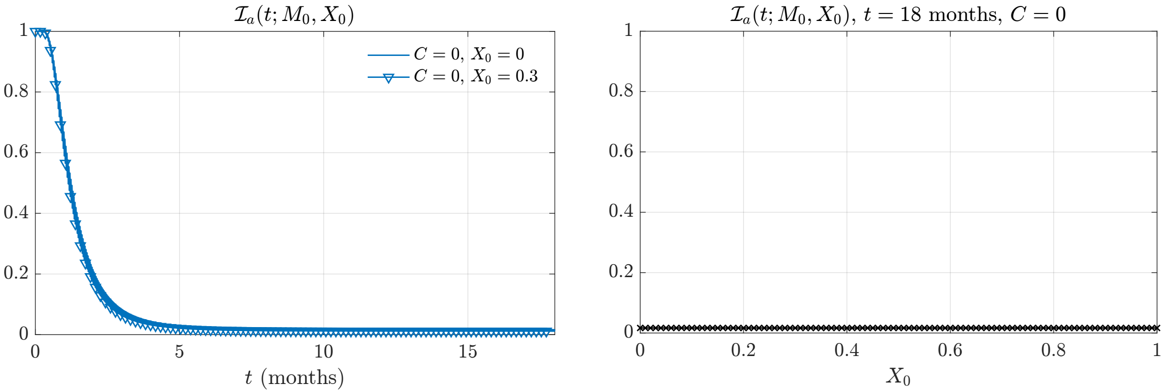
Prediction 2: $C > 0 \implies$ persistent increase in adoption rate (a_t)



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

$$\frac{\partial}{\partial C}\mathcal{I}_a(t; M_0, 0) \geq 0.$$

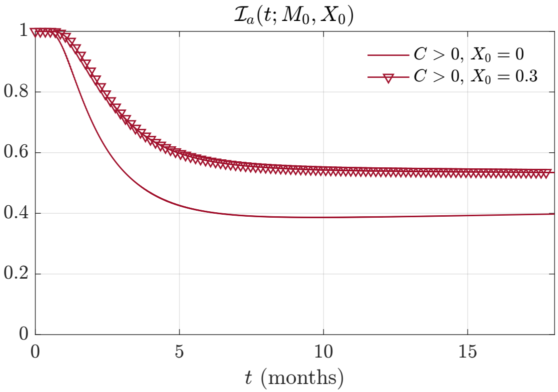
Prediction 3: $C > 0 \implies$ **state-dependence**

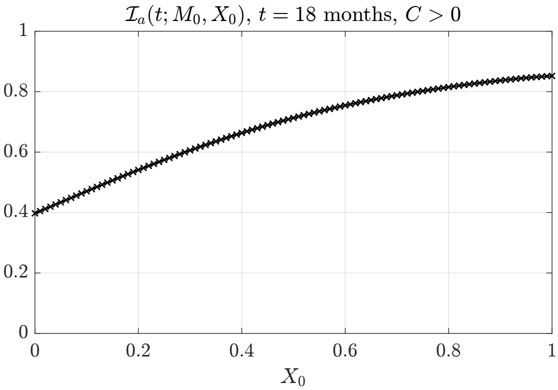


Numerical result: When $C > 0$, the IRF of the adoption rate a_t increases with X_0:

$$\frac{\partial}{\partial X_0} \mathcal{I}_a(t; M_0, X_0) > 0.$$

Prediction 3: $C > 0 \implies$ state-dependence





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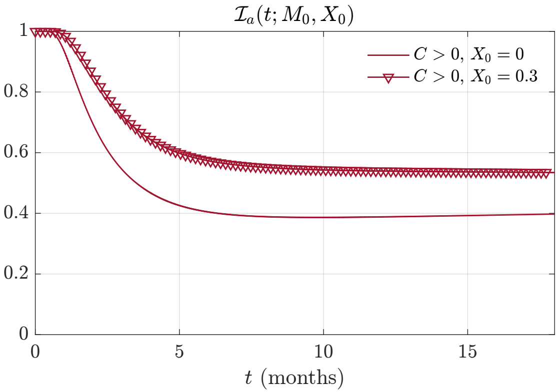

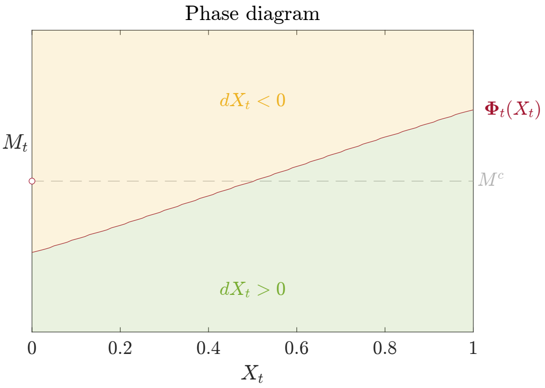

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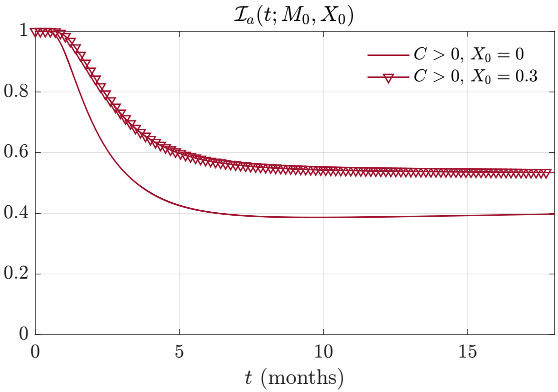

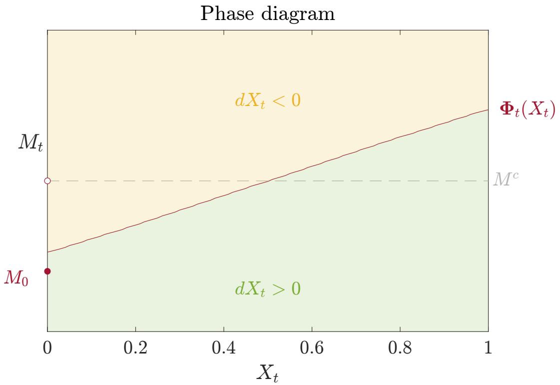

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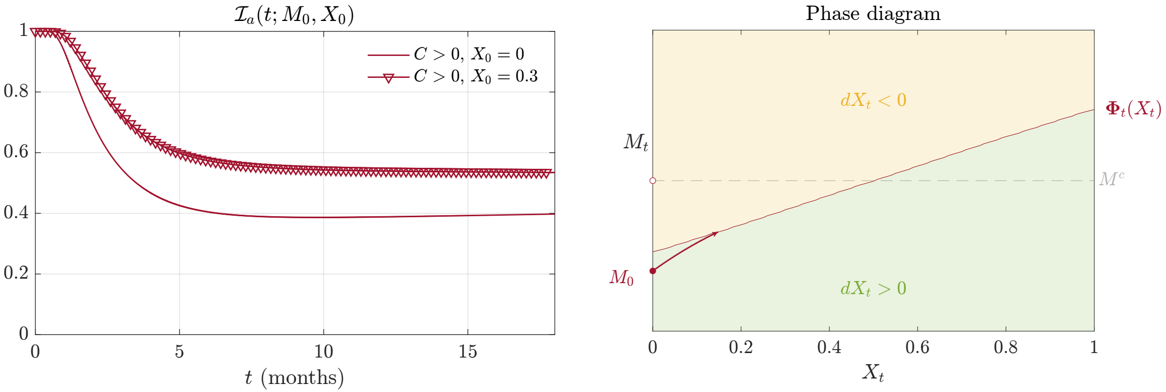

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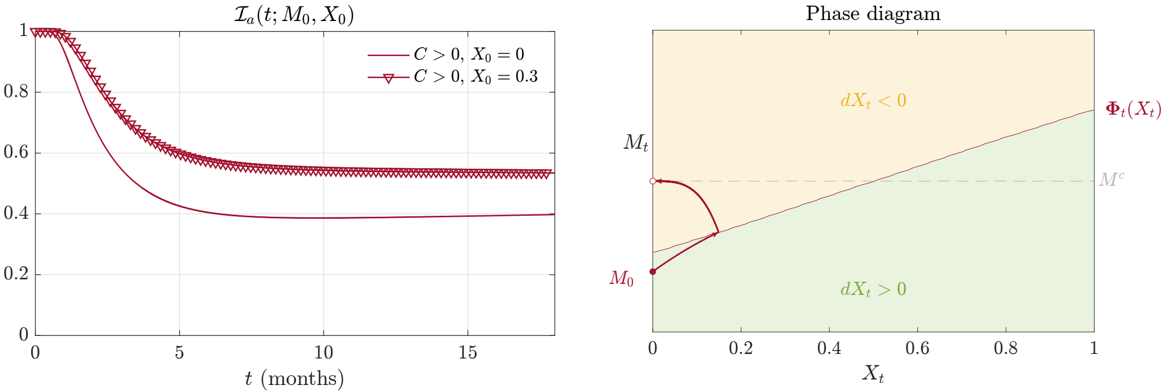

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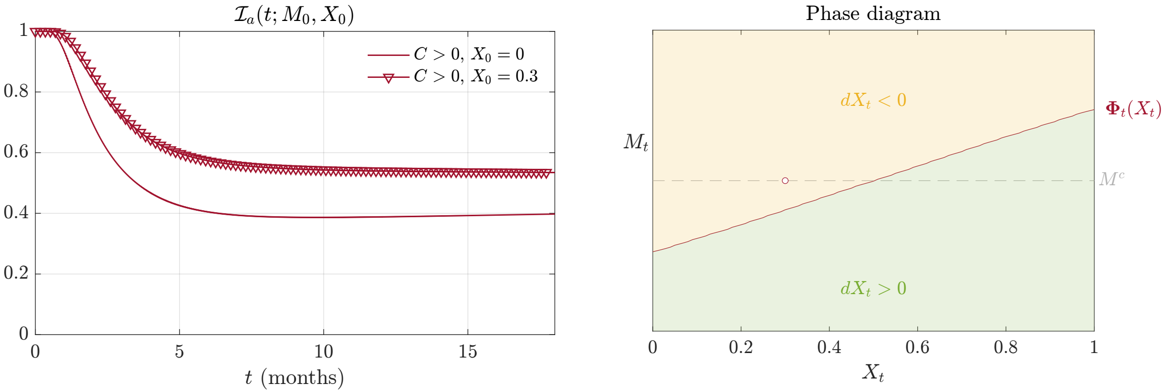

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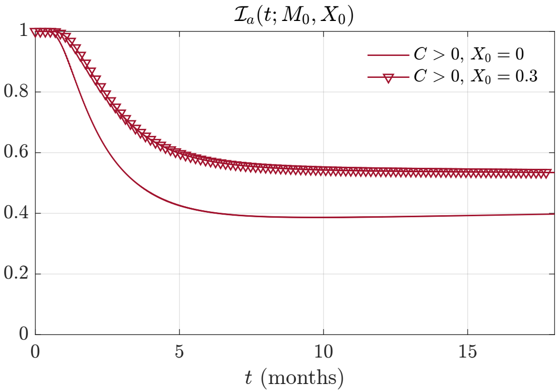

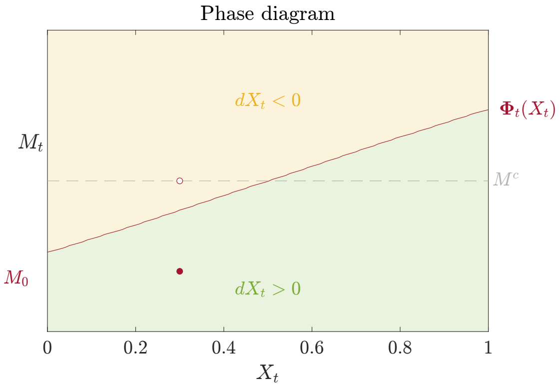

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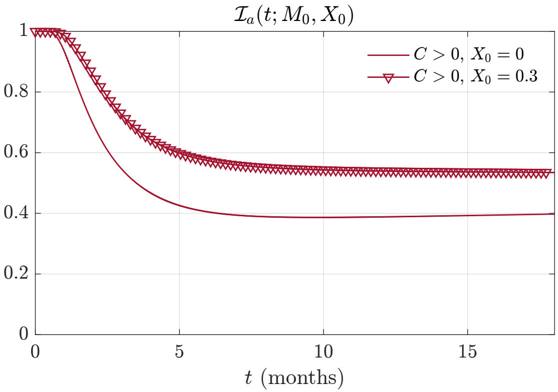

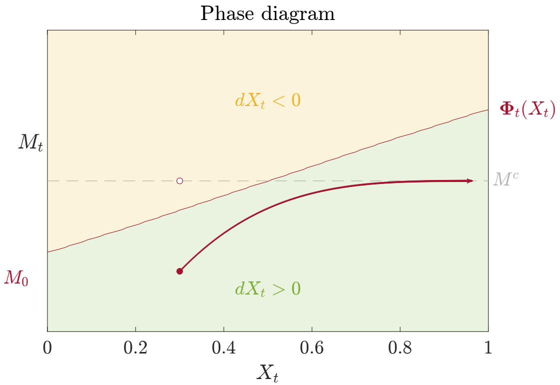

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Summary

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

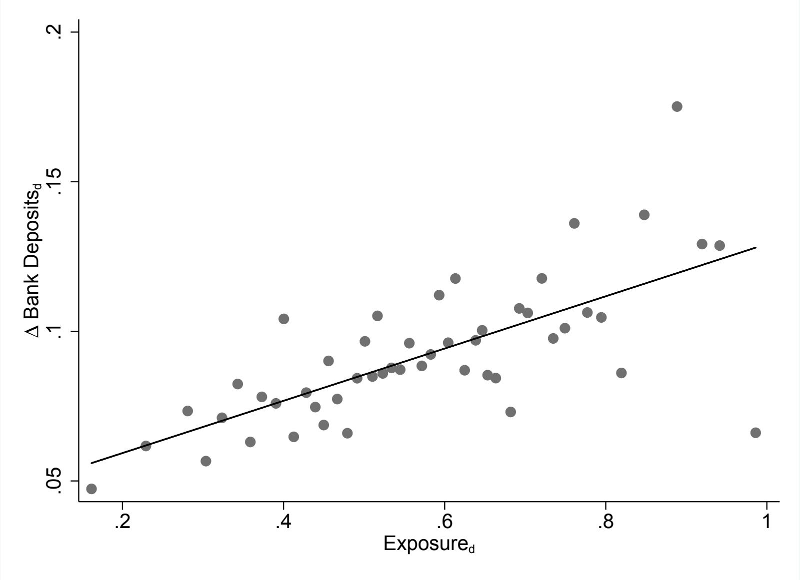
commercial banks handling cash distribution within districts

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

$$\text{Exposure}_d = 1 - \text{Chest share}_d$$

Validation of exposure measure

Table Other quarters Distribution Map



Main specification

$$\log\left(y_{d,t}\right) = \alpha_t + \alpha_d + \delta_t (\text{Exposure})_d + \Gamma_t' Y_d + \epsilon_{d,t}$$

d : district

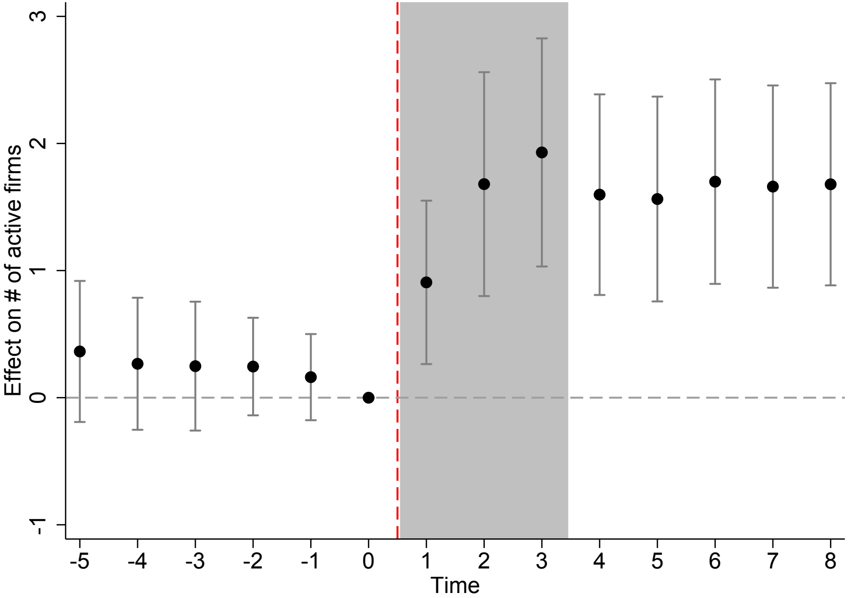
t : month (May 2016 to June 2017)

Y_d : district covariates (to ensure conditional balance) Table

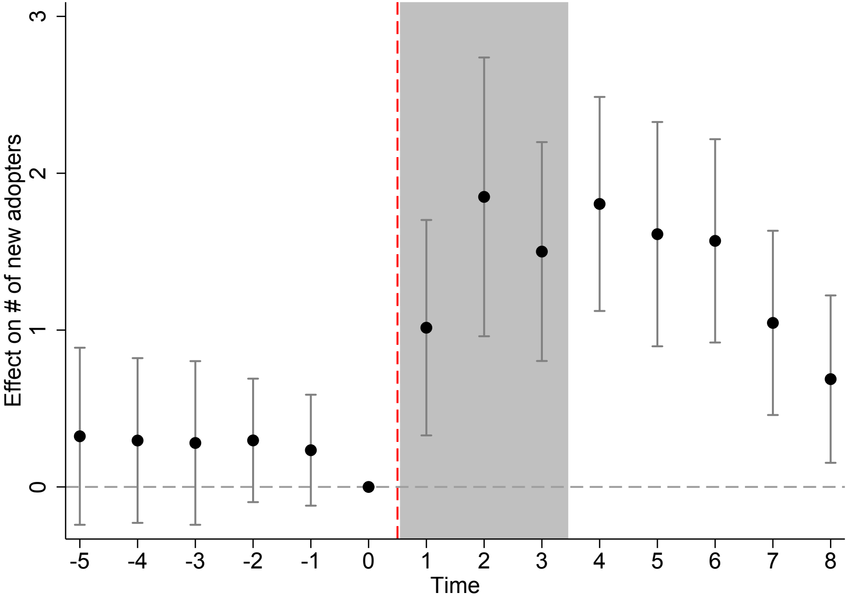
s.e. clustered by district

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

Table

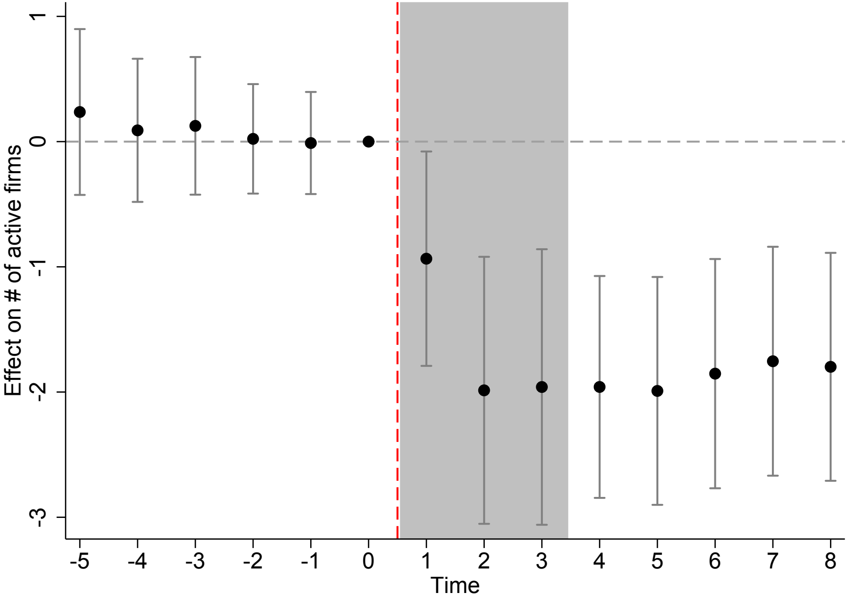
Instrumenting for initial adoption

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

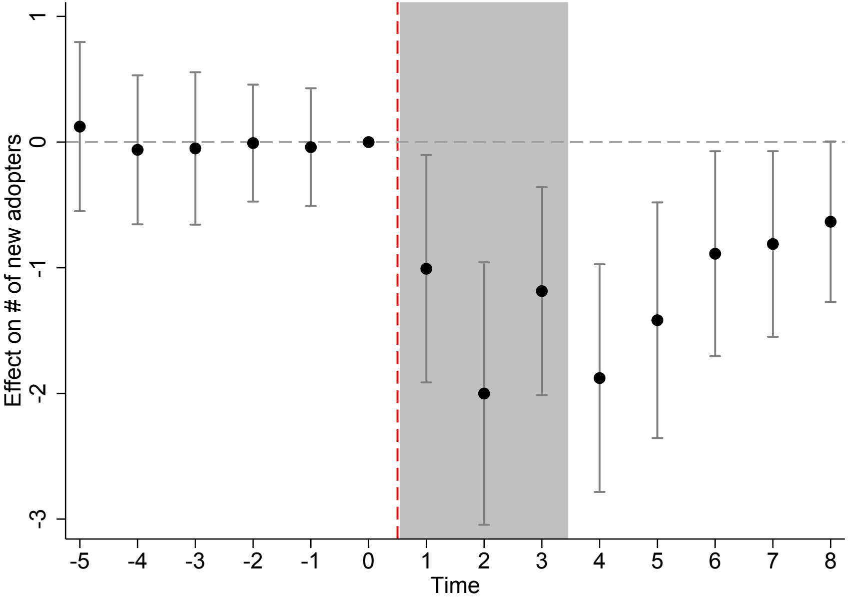
$$X_{d,t} = \alpha_t + \alpha_d + \delta_t D_d + \Gamma_t' Y_d + \epsilon_{d,t}$$

$$D_d = \text{min distance to the 5 largest pre-shock hubs}$$

Distance to hub and number of firms (P3)



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 θ + low k)

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

Model with low k + low $\theta \implies$ **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 $\implies$ **P1**, but not **P2** or **P3**

③ $C = 0$, but demand shock

Higher exposure predicts lower consumption Evidence

Alternative explanations (2/2)

④ $C = 0$, but adoption response driven by learning

Pre-Nov adopters: persistent increase in activity Evidence

Nov-Jan adopters: shock exposure predicts increase in activity from Feb to June Evidence

Index of social connectivity does not predict stronger response to shock Evidence

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 Evidence

- 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: SMM

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

8 moments from the panel of districts:

$$\begin{aligned}
\Delta_{t_0} X_{d,t} &= \beta + \gamma \mathbf{1}\{t \geq t_0 + 3\} + \delta X_{d,t_0} + \zeta \left(\mathbf{1}\{t \geq t_0 + 3\} \times X_{d,t_0}\right) + \epsilon_{d,t}, \\
\hat{var}_t(\Delta_{t_0} X_{d,t}) &= \eta + \kappa \mathbf{1}\{t \geq t_0 + 3\} + \mu_t, \\
\hat{var}_d(\Delta_{t_0} X_{d,t}) &= \nu + \omega_d,
\end{aligned}$$

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

Estimation

5 structural parameters: SMM

C	Complementarities
k	Max switching rate
S	Shock to cash demand
M^e	Returns to e when $X_t = 0$
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$$
\begin{aligned}
\Delta_{t_0} X_{d,t} &= \beta + \gamma \mathbf{1}\{t \geq t_0 + 3\} + \delta X_{d,t_0} + \zeta \left(\mathbf{1}\{t \geq t_0 + 3\} \times X_{d,t_0} \right) + \epsilon_{d,t}, \\
\hat{var}_t(\Delta_{t_0} X_{d,t}) &= \eta + \kappa \mathbf{1}\{t \geq t_0 + 3\} + \mu_t, \\
\hat{var}_d(\Delta_{t_0} X_{d,t}) &= \nu + \omega_d,
\end{aligned}
$$

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

Estimation

5 structural parameters: SMM

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

8 moments from the panel of districts:

$$\begin{aligned}
\Delta_{t_0} X_{d,t} &= \beta + \gamma \mathbf{1}\{t \geq t_0 + 3\} + \delta X_{d,t_0} + \zeta \left(\mathbf{1}\{t \geq t_0 + 3\} \times X_{d,t_0}\right) + \epsilon_{d,t}, \\
\hat{var}_t(\Delta_{t_0} X_{d,t}) &= \eta + \kappa \mathbf{1}\{t \geq t_0 + 3\} + \mu_t, \\
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\end{aligned}$$

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

Estimation

5 structural parameters: SMM

C	Complementarities	$\to \gamma$
k	Max switching rate	$\to \kappa$
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\hat{var}_d(\Delta_{t_0} X_{d,t}) &= \nu + \omega_d,
\end{aligned}$$

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

Estimation

5 structural parameters: SMM

C	Complementarities	$\to \gamma$
k	Max switching rate	$\to \kappa$
S	Shock to cash demand	$\to \beta$
M^e	Returns to e when $X_t = 0$	$\to \nu$
σ	Volatility of innovations to M_t	$\to \xi$

8 moments from the panel of districts:

$$\begin{aligned}
\Delta_{t_0} X_{d,t} &= \beta + \gamma \mathbf{1}\{t \geq t_0 + 3\} + \delta X_{d,t_0} + \zeta \left(\mathbf{1}\{t \geq t_0 + 3\} \times X_{d,t_0} \right) + \epsilon_{d,t}, \\
\hat{var}_t(\Delta_{t_0} X_{d,t}) &= \eta + \kappa \mathbf{1}\{t \geq t_0 + 3\} + \mu_t, \\
\hat{var}_d(\Delta_{t_0} X_{d,t}) &= \nu + \omega_d,
\end{aligned}$$

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

Results

Parameter		Estimate	Standard error
C	Complementarities	0.063	(0.004)
k	Max switching rate	0.163	(0.041)
S	Shock to cash demand	0.246	(0.047)
M^e	Returns to e when $X_t = 0$	0.970	(0.004)
σ	Volatility of innovations to M_t	0.039	(0.011)

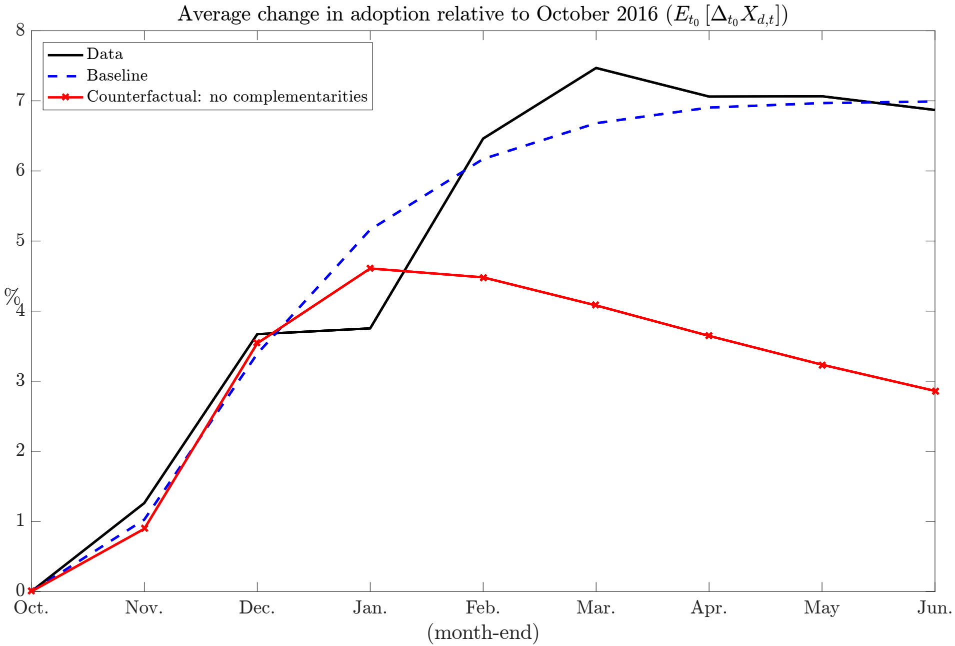
- Reject null of $C = 0$

Model fit

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$\times$ 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
%
0
1
2
3
4
5
6
7
8
Oct.
Nov.
Dec.
Jan.
Feb.
Mar.
Apr.
May
Jun.
(month-end)

Counterfactuals

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

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

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

	Baseline	Alternative policy interventions			
		$g = 0$	$g = 0.10$	$g = 0.25$	$g = 0.5$
Shock size (p.p.)	24.6	21.0	18.3	16.8	14.2
Shock HL (months)	0.8	1.1	1.3	1.4	1.6
$\mathbb{E}\left[\Delta X_d\right]$ (p.p.)	7.2	8.3	8.3	8.2	7.8
$sd\left[\Delta X_d\right]$ (p.p.)	26.4	36.7	34.6	28.7	24.8

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

<u>but</u> temporary intervention also exacerbate initial adoption differences

Appendix

Equilibrium characterization

Back

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:*

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

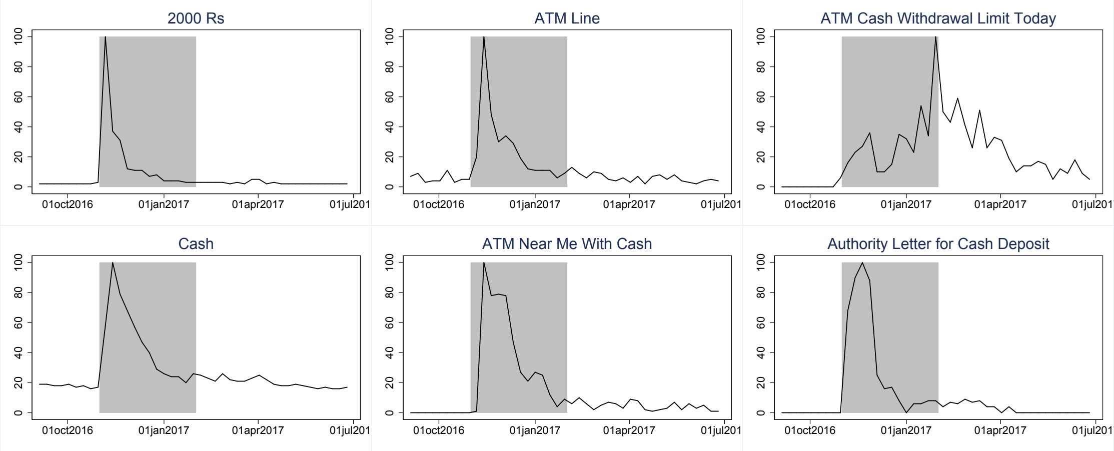
Then the equilibrium exists and is unique. There exists a function $\Phi_t(X_t)$ such that:

$$a_t(M_t, X_t) = 1 \quad \iff \quad M_t \leq \Phi_t(X_t).$$

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

Back



Microfoundations: two-sided market and multi-homing (1/3)

Back

Consumers allocate deposits to cash L_t^c and the electronic wallet L_t^e subject to:

$$
\begin{aligned}
\max_{C_t^c, C_t^e, L_t^c, L_t^e} \quad & X_t \left(\zeta C_t^e + (1-\zeta) C_t^c\right) + (1 - X_t) C_t^c - \frac{1}{2\gamma} \left(L_t^e - L^e\right)^2 \\
\text{s.t.} \quad L_t^c + L_t^e & \leq D \quad [\lambda_t] \\
L_t^c & \leq L_t \quad [\mu_t] \\
C_t^c & \leq L_t^c \quad [\nu_t^c] \\
C_t^e & \leq L_t^e \quad [\nu_t^e]
\end{aligned}
$$

X_t is the fraction of firms that accept <u>both</u> the wallet, and cash.

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

Microfoundations: two-sided market and multi-homing (2/3)

Back

Firm profits are given by:

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

e now denotes a firm that accepts <u>both</u> electronic money and cash.

Microfoundations: two-sided market and multi-homing (3/3)

Back

Assume that $D \geq L_t + L^e + \gamma\zeta$. With $L_t^e = C_t^e$, $L_t^c = C_t^c$, we have:

$$\begin{aligned} C_t^c + C_t^e &< D \\ C_t^e &= L^e + \gamma\zeta X_t \\ C_t^c &= L_t \end{aligned}$$

Therefore:

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

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

$$C = \gamma\zeta^2.$$

Estimation methodology: SMM

Back

Objective function:

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

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

Use the optimal weighting matrix:

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

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

$$var \left(\hat{\Xi} \right) = \frac{1}{B-1} \sum_{b=1}^{B} \left(\hat{\Xi}_b - \hat{\Xi} \right)' \left(\hat{\Xi}_b - \hat{\Xi} \right).$$

Validation of exposure measure: table

Back

	Δ log(deposits)		Δ log(deposits$^{adj.}$)		Δ log(deposits^{N})	
	(1)	(2)	(3)	(4)	(5)	(6)
Chest Exposure	0.094***	0.083***	0.085***	0.075***	1.821***	1.621***
	[0.013]	[0.012]	[0.013]	[0.012]	[0.257]	[0.238]
log(Pre Deposits)		-0.035***		-0.035***		-0.677***
		[0.003]		[0.003]		[0.063]
% villages with ATM		0.023		0.020		0.445
		[0.040]		[0.042]		[0.769]
% villages with banks		-0.051**		-0.051**		-1.000**
		[0.023]		[0.024]		[0.449]
Rural Pop./Total Pop.		-0.063***		-0.070***		-1.224***
		[0.016]		[0.017]		[0.317]
log(population)		0.036***		0.035***		0.707***
		[0.003]		[0.003]		[0.068]
Observations	512	512	512	512	512	512
R-squared	0.118	0.313	0.099	0.290	0.118	0.313
District Controls		✓		✓		✓

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

Back

	(1) 2016q4	(2) 2016q3	(3) 2016q2	(4) 2016q1	(5) 2015q4	(6) 2015q3
$(\text{Exposure})_d$	1.621***	-0.404	0.476**	0.137	0.163	0.342
	[0.238]	[0.260]	[0.236]	[0.234]	[0.268]	[0.255]
Observations	512	512	512	512	512	512
R-squared	0.313	0.027	0.026	0.162	0.020	0.054
District Controls	✓	✓	✓	✓	✓	✓

	(7) 2015q2	(8) 2015q1	(9) 2014q4	(10) 2014q3	(11) 2014q2	(12) 2014q1
$(\text{Exposure})_d$	-0.040	0.315	0.345	-0.734***	0.165	0.012
	[0.231]	[0.240]	[0.291]	[0.280]	[0.257]	[0.269]
Observations	512	512	512	512	512	512
R-squared	0.044	0.061	0.017	0.037	0.100	0.124
District Controls	✓	✓	✓	✓	✓	✓

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

Balance Analysis

Back

Dependent variable:	mean	univariate OLS		baseline controls	
		coeff.	R^2	coeff.	R^2
Log(Pre Deposits)	11.083	-1.290***	0.054		
	(0.048)	(0.273)			
% villages with ATM	0.036	0.090***	0.040		
	(0.004)	(0.023)			
# Bank Branches per 1000's	0.047	0.002	0.000	0.015	0.234
	(0.002)	(0.012)		(0.012)	
# Agri Credit Societies per 1000's	0.045	-0.016	0.001	0.016	0.062
	(0.004)	(0.027)		(0.022)	
% villages with banks	0.085	0.131***	0.033	0.058	0.580
	(0.006)	(0.036)		(0.036)	
Log(Population)	14.376	-0.501**	0.015	0.304	0.481
	(0.035)	(0.208)		(0.199)	
Literacy rate	0.622	-0.029	0.003	-0.001	0.227
	(0.005)	(0.025)		(0.025)	
Sex Ratio	0.946	0.008	0.001	-0.009	0.063
	(0.003)	(0.015)		(0.017)	
Growth Rate	0.208	-0.219	0.014	-0.232	0.021
	(0.016)	(0.139)		(0.171)	
Working Pop./Total Pop.	0.410	0.026	0.005	0.010	0.075
	(0.003)	(0.016)		(0.017)	
Distance to State Capital(kms.)	0.215	0.035	0.002	0.026	0.016
	(0.006)	(0.032)		(0.032)	
Rural Pop./Total Pop.	0.746	0.170***	0.034	0.046	0.464
	(0.008)	(0.047)		(0.039)	

State dependence: within district

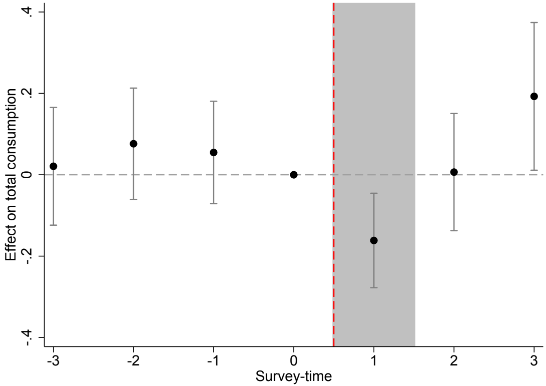
Back

	Log(# transactions)		Log(amount)	
	(1)	(2)	(3)	(4)
$\mathbf{1}(t \geq t_0) \times \mathbf{1}(\text{Any adopter}_d)$	2.803***		4.864***	
	(0.246)		(0.346)	
$\mathbf{1}(t \geq t_0) \times \log(\text{Amount of transactions}_d)$		0.281***		0.230***
		(0.028)		(0.052)
Month f.e.	✓	✓	✓	✓
District f.e.	✓	✓	✓	✓
District Controls		✓		✓
Observations	5,780	5,780	5,780	5,780
R-squared	0.609	0.603	0.578	0.570
Number of districts	578	578	578	578

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

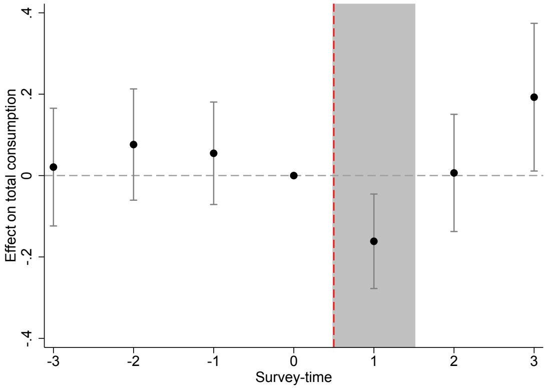
How persistent was the shock?

Back



The response of consumption

Back



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

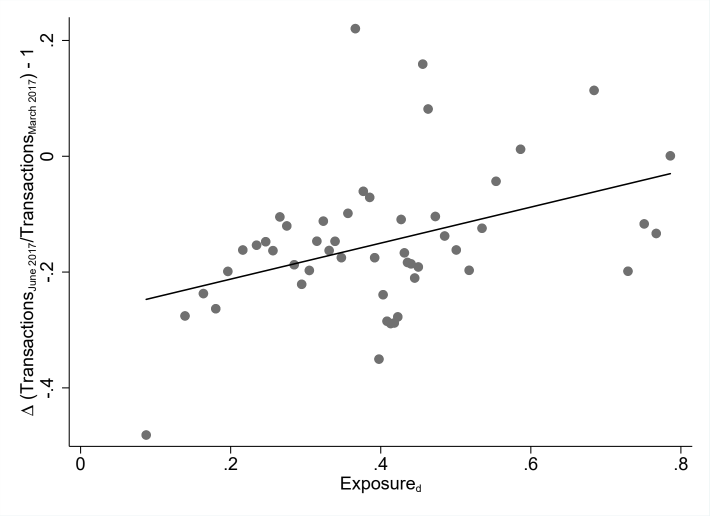
Back

VARIABLES	(1) amount	(2) amount	(3) amount	(4) amount	(5) transactions	(6) transactions	(7) transactions	(8) transactions
SR × exposure		1.651***		1.660**		0.721**		0.733**
		[0.600]		[0.645]		[0.317]		[0.339]
LR × exposure		1.276**		1.244*		0.415		0.404
		[0.620]		[0.650]		[0.261]		[0.278]
post × exposure	1.370**		1.348**		0.492*		0.486*	
	[0.598]		[0.633]		[0.268]		[0.287]	
post × exposure × high sci			-0.883				-0.643	
			[2.056]				[0.666]	
post × high sci			0.903	0.903			0.579	0.579
			[1.316]	[1.316]			[0.390]	[0.390]
SR × exposure × high sci				-1.270				-0.826
				[2.098]				[0.737]
LR × exposure × high sci				-0.754				-0.582
				[2.056]				[0.651]
Observations	132,608	132,608	132,552	132,552	132,608	132,608	132,552	132,552
R-squared	0.543	0.544	0.544	0.544	0.575	0.575	0.575	0.575
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓
Month f.e.	✓	✓	✓	✓	✓	✓	✓	✓
District Controls × Month f.e.	✓	✓	✓	✓	✓	✓	✓	✓

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

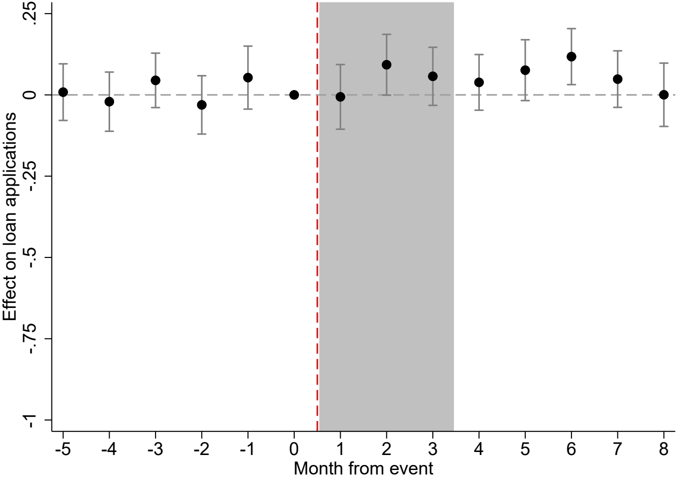
Learning: Nov-Jan adopters

Back



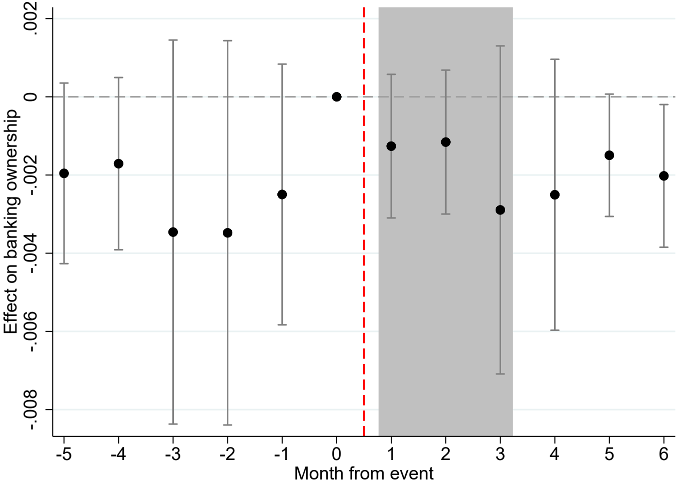
The reflection problem (1/3)

Back



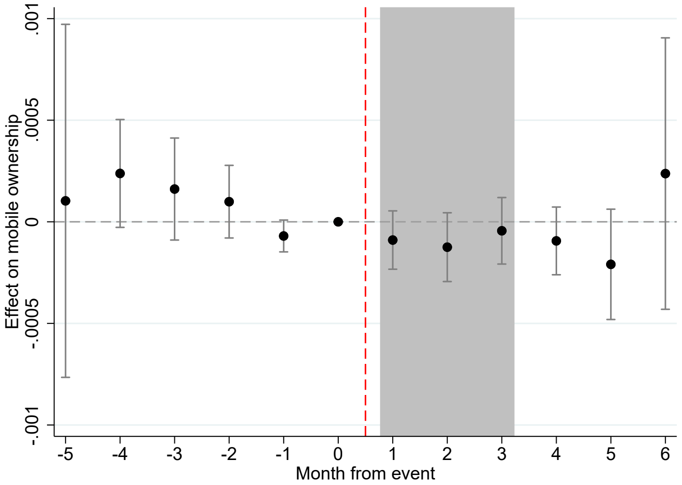
The reflection problem (2/3)

Back



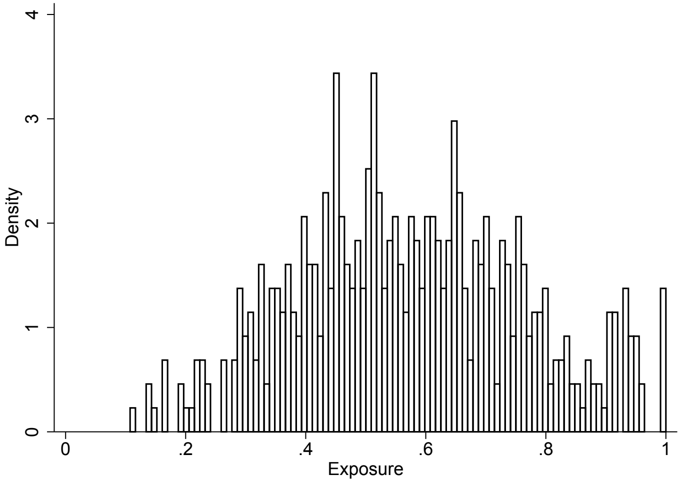
The reflection problem (3/3)

Back



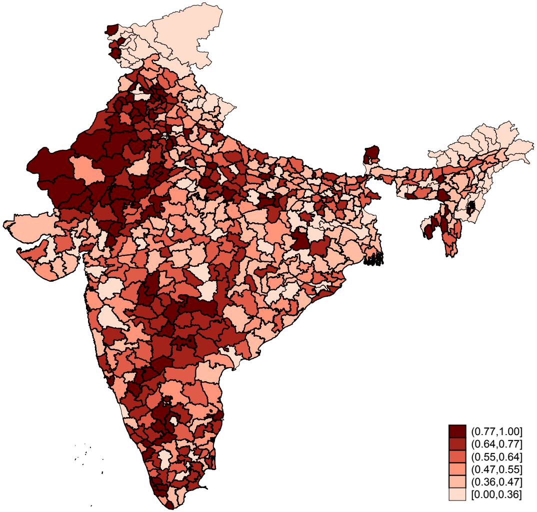
Histogram of exposure

Back



Map of exposure

Back



Results excluding individual states

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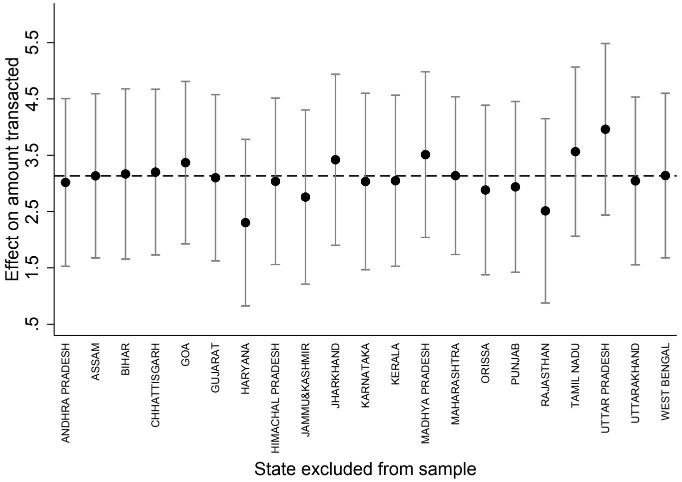
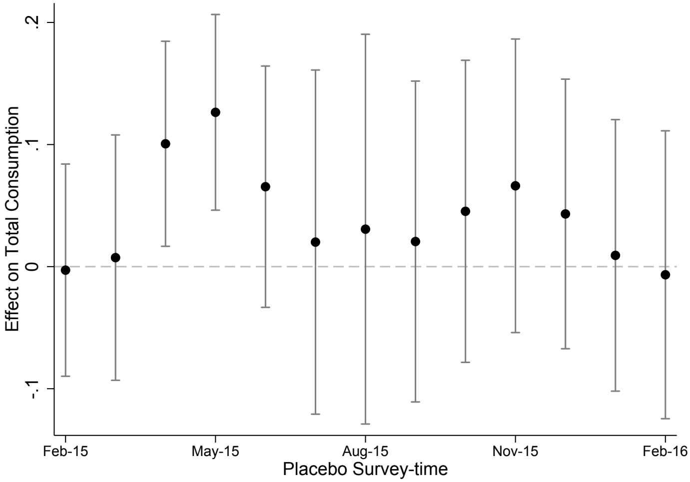


Placebo using consumption

Back



Traditional electronic payments: intensive margin

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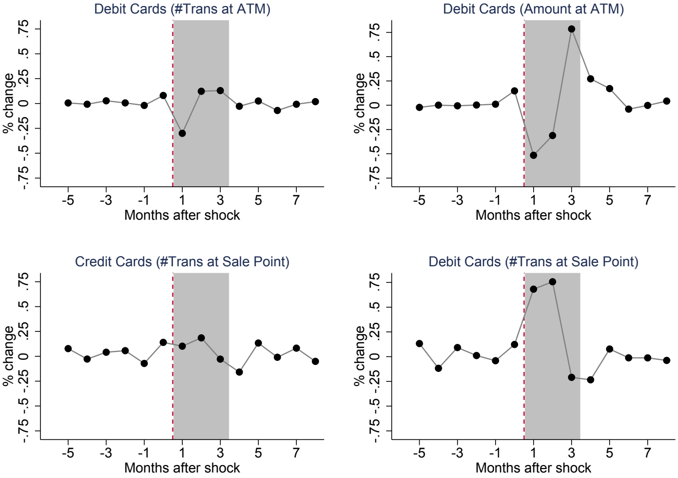

Traditional electronic payments: extensive margin

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