

# **“Strategic Complementarities in a Dynamic Model of Technology Adoption”**

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Discussion by Nicolas Crouzet

Kellogg

## Overview: the adoption of network technologies

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Step 1: Model of technology adoption with strategic complementarities

Decentralized equilibrium + optimal planning problem

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Step 1: Model of technology adoption with strategic complementarities

Decentralized equilibrium + optimal planning problem

Step 2: Data on digital payment app in Costa-Rica

Can observe adoption *within social networks* (neighborhood, coworkers, family)

# Roadmap

1. The adoption of digital payments in India
2. The model
3. Mapping the model to the data

# 1. The adoption of digital payments in India



# Context: the 2016 Indian Demonetization

Cash shortage

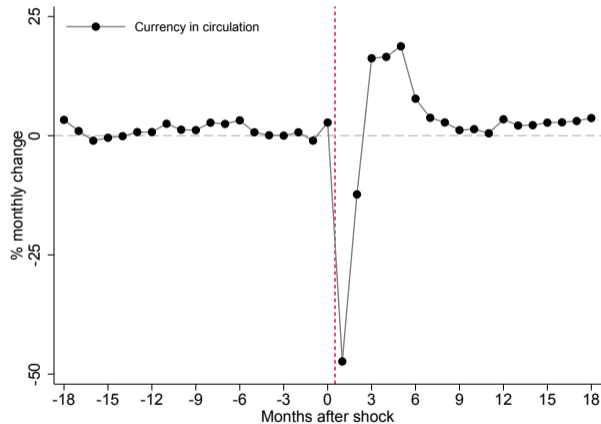
unexpected

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Adoption of an electronic wallet

B2C transactions



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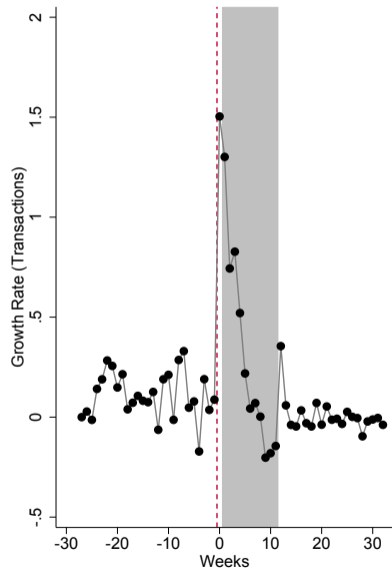
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# Model

Firm  $i \in [0, 1]$ :

$$\pi_{i,t} = \begin{cases} M_t & \text{if } x_{i,t} = c & \text{(cash)} \\ \theta_0 + \theta_n N_t & \text{if } x_{i,t} = e & \text{(e-wallet)} \end{cases}$$

$M_t$  cash-based demand; exogenous, AR

$$N_t = \int \mathbf{1}\{x_{i,t} = e\} di = \text{number of adopters}$$

Firm  $i$  chooses a switching rate  $c \leftrightarrow e, \tilde{k}_{i,t} \in [0, k]$ , to maximize NPV of  $\pi_{i,t}$   
subject to law of motion for  $(M_t, N_t)$

# Adoption rules

Equilibrium: aggregate law of motion for  $N_t$   $\leftrightarrow$  optimal switching rate  $\tilde{k}_{i,t}$

**Result:** The equilibrium exists and is unique. Firms switch  $c \rightarrow e$  at max rate  $k$ , if and only if:

$$M_t \leq \underline{M}(N_t; \theta_n),$$

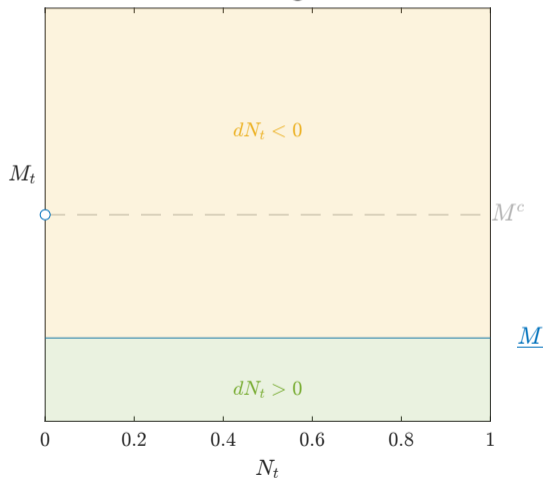
where:

$$\theta_n = 0 : \underline{M}(N_t; \theta_n) = \underline{M},$$

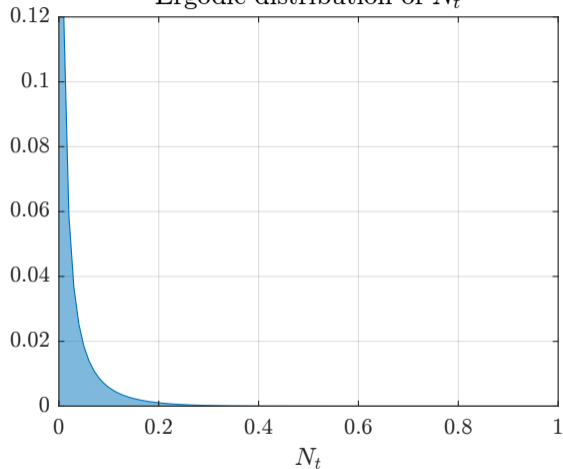
$$\theta_n > 0 : \underline{M}(N_t; \theta_n).$$

# Testing for complementarities: endogenous persistence

Phase diagram



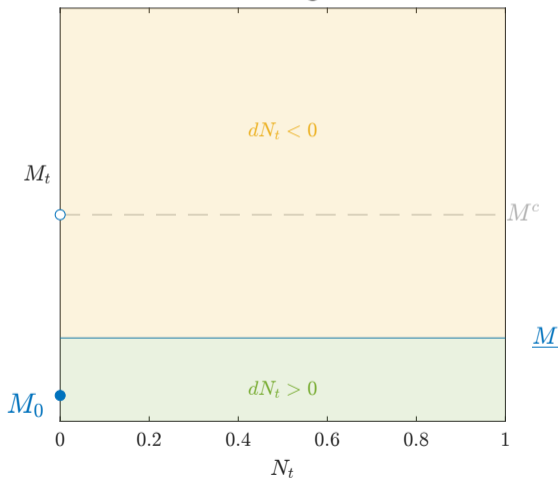
Ergodic distribution of  $N_t$



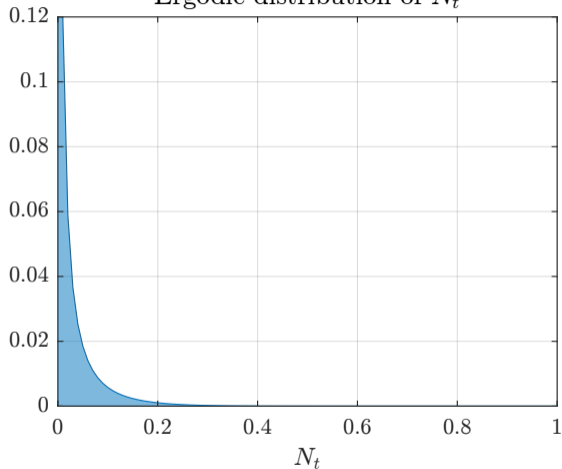
No complementarities ( $\theta_n = 0$ )

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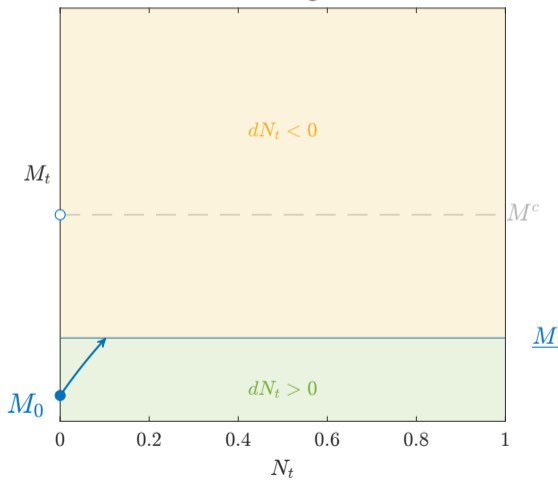
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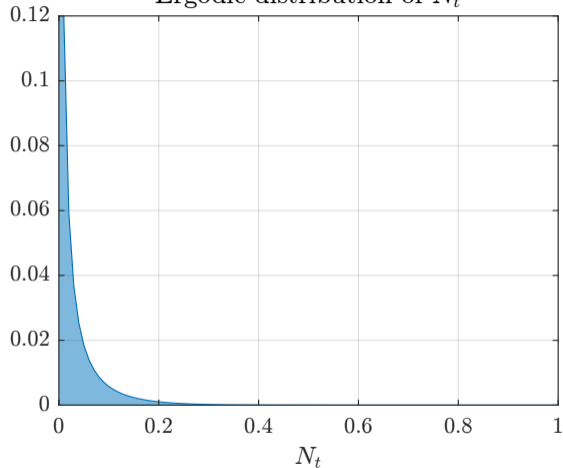
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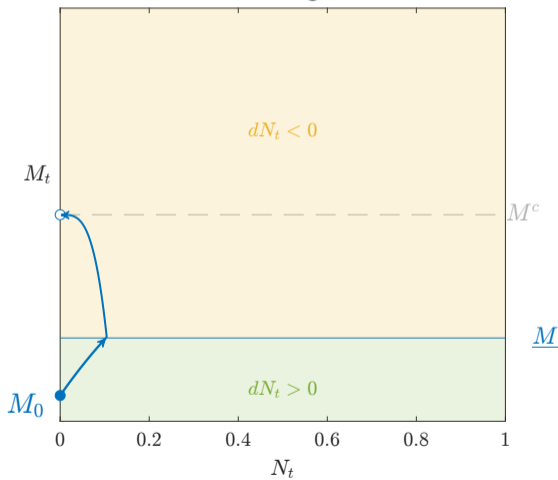
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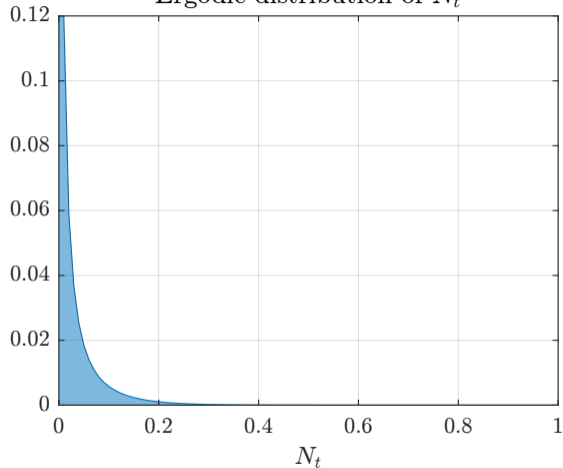
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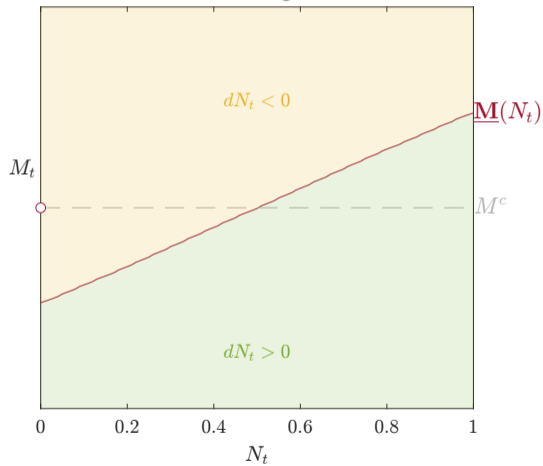


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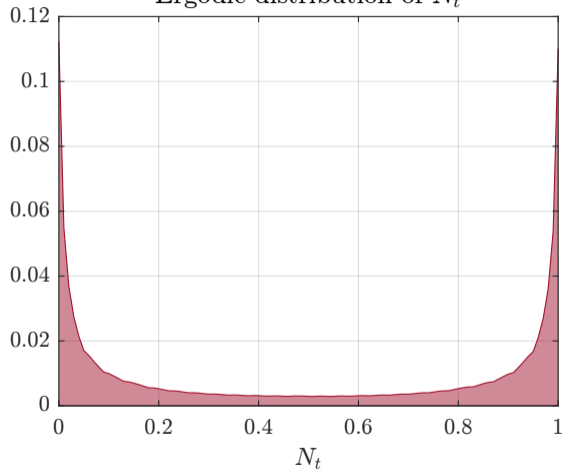


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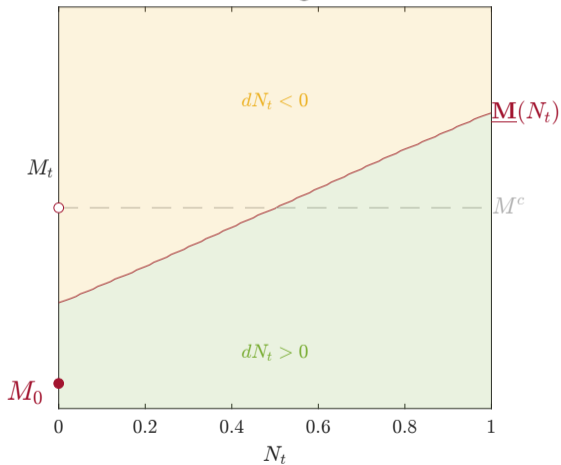
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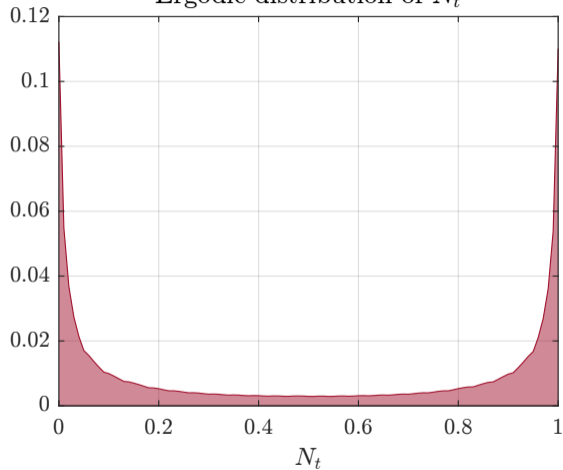
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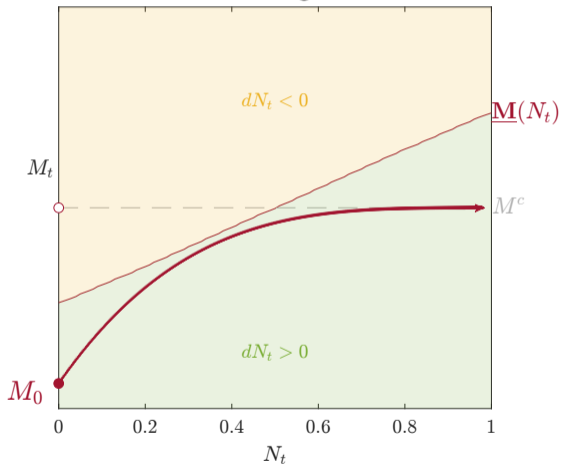
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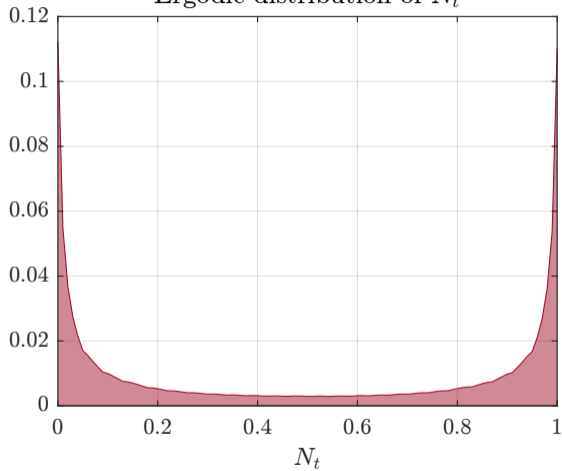
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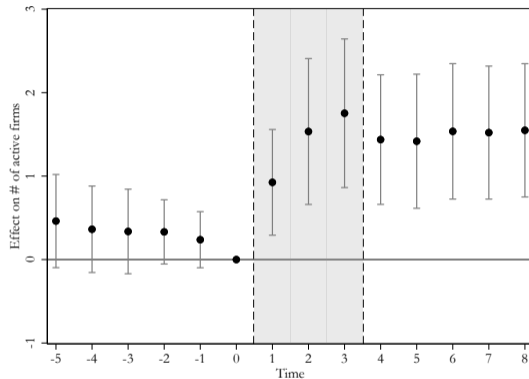


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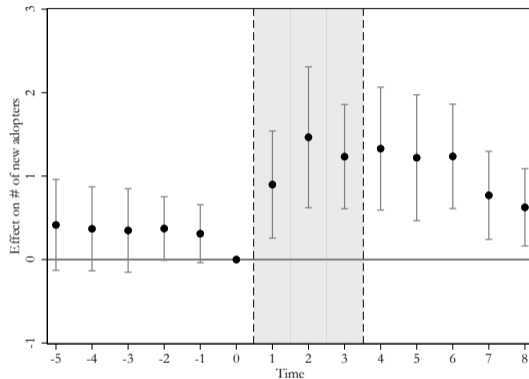


District  $d$ , quarter  $t$

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

$y_{d,t}$  : total # of active firms

# Testing for complementarities: endogenous persistence



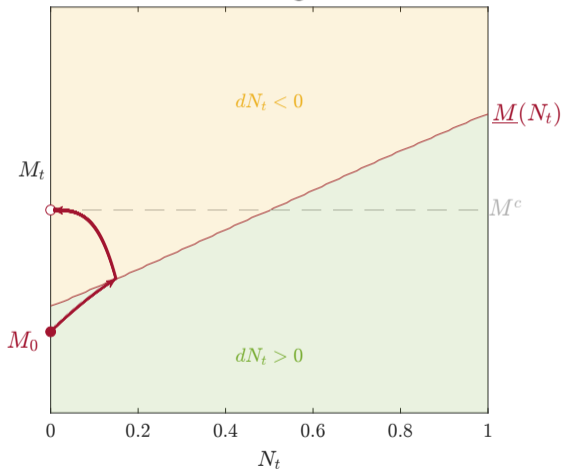
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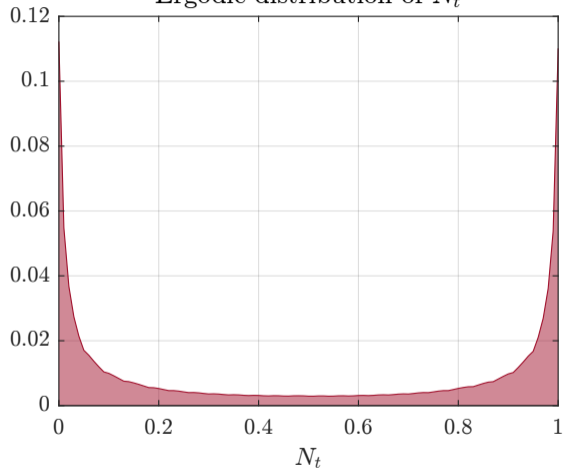
$y_{d,t}$  : # of newly active firms

# Testing for complementarities: state-dependence

Phase diagram



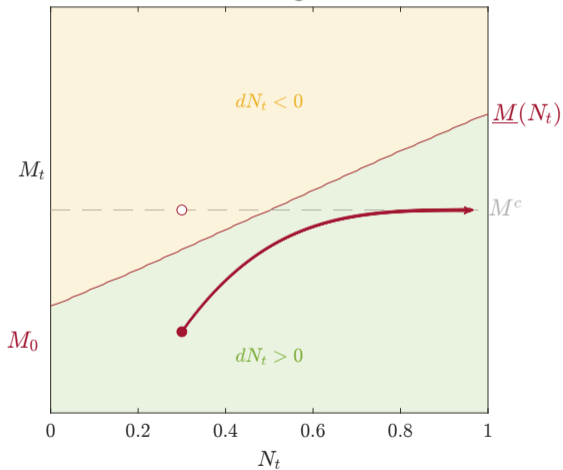
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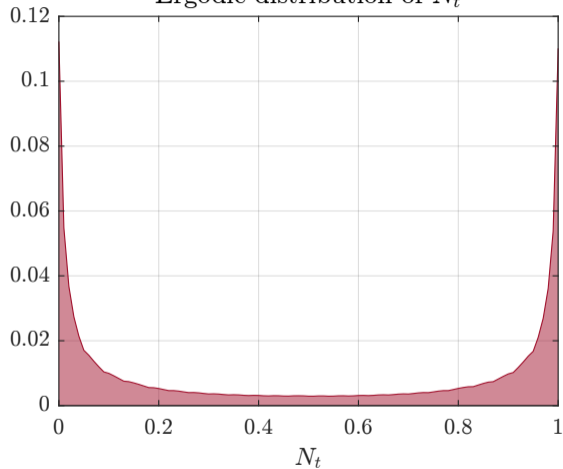
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Ergodic distribution of  $N_t$



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## Key take-aways

In our setting

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Dynamic tests for strategic complementarities

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## Beyond our setting

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The limits of a "big push"

persistent increase in average adoption across networks

*at the cost of* more dispersion

## 2. The model

## Comparing the models

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		<b>This paper</b>	<b>CGM</b>
<b>Flow benefits</b>	No adoption	0	$M_t$
	Adoption	$x_{i,t} (\theta_0 + \theta_n N_t)$	$\theta_0 + \theta_n N_t$
<b>Lock-in after adoption</b>		Yes	No
<b>Friction</b>		Fixed cost $c$	Switching intensity $\tilde{k}_{i,t} \leq k$

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Which of these differences is economically important?

**This paper :** only idiosyncratic shocks

**CGM :** only aggregate shocks

**Does aggregate risk matter for understanding technology adoption?**

# Does aggregate risk matter for understanding technology adoption?

## "Phase shifts"

Sudden adoption of "dormant" technology

Sudden discarding of "dominant" technology

Aggregate risk *can* generate this

Idiosyncratic risk generates gradual and permanent diffusion

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See global games

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Important for counterfactuals and policy analysis

# Combining aggregate and idiosyncratic risk

## CGM

As  $M_t$  crosses  $\underline{\mathbf{M}}(N_t; \theta_n)$ , mass  $kdt$  of firms change adoption decisions at once — “phase shift”

⇒ drift of  $N_t$  is a discontinuous function of  $M_t$

## This paper

Mass of firms revising their adoption decision remains small — no “phase shift”

Distribution of adopters follows a standard KFE

## Combining the two

If sufficiently large idiosyncratic shocks,  $N_t$  might become a standard diffusive process

$\underbrace{\text{Phase shifts} + \text{unicity}}_{\text{CGM}} + \underbrace{\text{tractability}}_{\text{this paper}}$

### 3. Mapping the model to the data

# Measuring strategic complementarities

**Model**

$$\log(\xi_{i,t}) = \frac{1}{1+p} \log(\theta_0 + \theta_n N_t) + \frac{1}{1+p} \log(x_{i,t}) \quad (1)$$

$$\Delta \log(\xi_{i,t}) = \lambda_t + \psi \Delta S_{i,t} + \tilde{\theta} \Delta N_{i,t} + \varepsilon_{i,t} \quad (2)$$

**Data**

$S_{i,t}$  = # of people in  $i$ 's social network

$N_{i,t}$  = % of people in  $i$ 's social network using the app

$$\theta_n \overset{?}{\leftrightarrow} \tilde{\theta}$$

# The reflection problem [Manski, 1993]

**Model**

$$\log(\xi_i) = \theta_n N_i + \gamma \text{age}_i + \varepsilon_i$$
$$N_i = \mathbb{E} [\log(\xi_j) | i\text{'s network, age}_i]$$

# The reflection problem [Manski, 1993]

$$\begin{aligned} \text{Model} \quad \log(\xi_i) &= \theta_n N_i + \gamma \text{age}_i + \varepsilon_i \\ N_i &= \mathbb{E} [\log(\xi_j) | i\text{'s network, age}_i] \\ \Rightarrow N_i &= \frac{\gamma}{1 - \theta_n} \text{age}_i \end{aligned}$$

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Do mass layoff regressions address this problem?

Choice of new firm might be driven by correlated characteristics among coworkers

# Estimating the model

Model is calibrated

$\theta_n \approx \tilde{\theta}$  + match median neighborhood adoption path

Resulting model  $\approx$  typical neighborhood

Could instead fit the distribution of adoption across neighborhoods:  $\mathbb{E}_t(N_{n,t}), \sigma_t(N_{n,t}), \dots$

Need neighborhood fixed effects in the model; can use  $N_{n,0}, \theta_0^{(n)}, U^{(n)}$

Useful to tackle policy questions about *aggregate* adoption

Calibrated model = complementarities + learning

What identifies the learning component?

i.e. what features of the data does the complementarities-only model fail to match?

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## What more is there to do?

Where is  $\theta_n > 0$  coming from?

Two-sided markets

Social learning

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What are the broader implications of  $\theta_n > 0$ ?

Spillovers to consumption, investment

Competition, concentration, regulation

[Higgins, 2022]