"Strategic Complementarities in a Dynamic Model of Technology Adoption"

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Discussion by Nicolas Crouzet

Kellogg
Overview: the adoption of network technologies

Theory: decisions to adopt are complements across users

\[\text{[Katz and Shapiro 1986, Farrell and Saloner 1986]}\]

\[\Rightarrow\]

\[\text{coordination problems}\]

In practice, how important are these coordination problems?

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)
Overview: the adoption of network technologies

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⇒ coordination problems

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In practice, how important are these coordination problems?

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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
- large
- temporary

Adoption of an electronic wallet
- B2C transactions

[Graph showing % monthly change in currency in circulation post-shock]
Context: the 2016 Indian Demonetization

Cash shortage
unexpected
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Adoption of an electronic wallet
B2C transactions
Firm \( i \in [0, 1] \):

\[
\pi_{i,t} = \begin{cases} 
M_t & \text{if } x_{i,t} = c \\
\theta_0 + \theta_n N_t & \text{if } x_{i,t} = e 
\end{cases}
\]

\( M_t \) cash-based demand; exogenous, AR

\( N_t = \int 1 \{x_{i,t} = e\} \, di \) = 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:

$$M_t \leq M(N_t; \theta_n),$$

where:

$$\theta_n = 0 : \quad M(N_t; \theta_n) = M,$$

$$\theta_n > 0 : \quad M(N_t; \theta_n).$$
Testing for complementarities: endogenous persistence

No complementarities ($\theta_n = 0$)
Testing for complementarities: endogenous persistence

Phase diagram

Ergodic distribution of $N_t$

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Complementarities ($\theta_n > 0$)
Testing for complementarities: endogenous persistence

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
District $d$, quarter $t$

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

$y_{d,t}$: # of newly active firms
Testing for complementarities: state-dependence

Phase diagram

\[\begin{align*}
\text{Complementarities (} \theta_n > 0) \\
M_t & \quad \text{d}N_t > 0 \\
M_0 & \quad \text{d}N_t < 0
\end{align*}\]

Ergodic distribution of \( N_t \)
Testing for complementarities: state-dependence

Phase diagram

Ergodic distribution of $N_t$

Complementarities ($\theta_n > 0$)
Key take-aways

In our setting

\[ \theta_n > 0; \text{ accounts for } \sim 1/2 \text{ of adoption response} \]
Key take-aways

In our setting

$\theta_n > 0$; accounts for $\sim 1/2$ of adoption response

Beyond our setting

Dynamic tests for strategic complementarities
- endogenous persistence
- positive state-dependence
Key take-aways

In our setting

\[ \theta_n > 0; \text{ accounts for } \sim 1/2 \text{ of adoption response} \]

Beyond our setting

Dynamic tests for strategic complementarities
  - endogenous persistence
  - positive state-dependence

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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<th>CGM</th>
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Which of these differences is economically important?

This paper: only idiosyncratic shocks
CGM: only aggregate shocks
Comparing the models

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**CGM**: only aggregate shocks
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 equilibrium this paper: multiple equilibria CGM: unique equilibrium aggregate shocks may eliminate multiplicity see global games but maybe not necessary: Alvarez, Lippi, Souganidis (2022) establish unicity in a closely related model important for counterfactuals and policy analysis
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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Equilibrium unicity

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Important for counterfactuals and policy analysis
Combining aggregate and idiosyncratic risk

**CGM**

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

$$\Rightarrow$$ 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

Phase shifts + unicity + tractability

CGM + this paper
3. Mapping the model to the data
Measuring strategic complementarities

Model

\[ \log(\xi_{i,t}) = \frac{1}{1+p} \log (\theta_0 + \theta_n N_{i,t}) + \frac{1}{1+p} \log(x_{i,t}) \]  

Data

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

\[ S_{i,t} = \text{# of people in } i\text{'s social network} \]

\[ N_{i,t} = \% \text{ of people in } i\text{'s social network using the app} \]

\[ \theta_n \leftrightarrow \tilde{\theta} \]
The reflection problem  [Manski, 1993]

Model  \[ \log(\xi_i) = \theta_n N_i + \gamma \text{age}_i + \varepsilon_i \]

\[ N_i = \mathbb{E} [\log(\xi_j) | \text{i's network, age}_i] \]
The reflection problem  

\[ \text{Model} \quad \log(\xi_i) = \theta_n N_i + \gamma \text{age}_i + \varepsilon_i \]

\[ N_i = \mathbb{E}[\log(\xi_j)|i's \ network, \ text{age}_i] \]

\[ \implies N_i = \frac{\gamma}{1 - \theta_n} \text{age}_i \]
The reflection problem  

[Manski, 1993]

Model

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\log(\xi_i) = \theta_n N_i + \gamma \text{age}_i + \varepsilon_i
\]

\[
N_i = \mathbb{E} [\log(\xi_j)|i's \ network, \ age_i]
\]

\[
\Rightarrow \ N_i = \frac{\gamma}{1 - \theta_n} \text{age}_i
\]

\[
\Rightarrow \hat{\theta}_{OLS} \equiv \frac{\text{cov}(\log(\xi_i), N_i)}{\text{var}(N_i)} = 1, \quad \text{even if } \theta_n \approx 0
\]

Even if we control for age, the model is not identified (\(N_i\) and \(\text{age}_i\) are colinear)

Do mass layoff regressions address this problem?

Choice of new firm might be driven by correlated characteristics among coworkers
The reflection problem  [Manski, 1993]

Model \[ \log(\xi_i) = \theta_n N_i + \gamma \text{age}_i + \varepsilon_i \]

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\log(\xi_i) = \theta_n N_i + \gamma \text{age}_i + \varepsilon_i \\
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Estimating the model

Model is calibrated

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

Resulting model approximates typical neighborhood

Could instead fit the distribution of adoption across neighborhoods: $E_t(N_{n,t}), \sigma_t(N_{n,t}), ...$

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?
Conclusion
Conclusion

What did I learn?

Optimal subsidy might not look like a "big push"

Individual technology use correlates with use by peers within granular social networks
Conclusion

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Individual technology use correlates with use by peers within granular social networks

What more is there to do?

Where is $\theta_n > 0$ coming from?

Two-sided markets
Social learning

[Jullien, Pavan, Rysman, 2021]
[Akbarpour, Malladi, Saberi, 2020]
Conclusion

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What more is there to do?
Where is $\theta_n > 0$ coming from?
- Two-sided markets
- Social learning

What are the broader implications of $\theta_n > 0$?
- Spillovers to consumption, investment
- Competition, concentration, regulation

[Jullien, Pavan, Rysman, 2021]
[Akbarpour, Malladi, Saberi, 2020]
[Higgins, 2022]