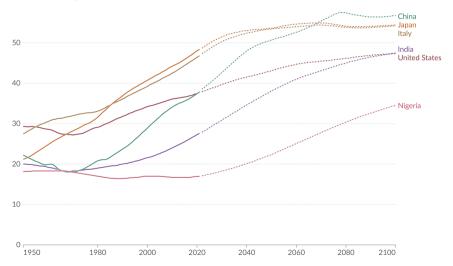
Demographics and Technology Diffusion: Evidence from Mobile Payments

Nicolas Crouzet (Northwestern) Pulak Ghosh (IIM Bangalore) Apoorv Gupta (Dartmouth, J-PAL) Filippo Mezzanotti (Northwestern, NBER)

Michigan Ross, Dec 2024

Median age

The median age splits the population into two equal groups, with as many people older than it as people younger than it. Future projections are based on the UN medium-fertility scenario.





Aging and Innovation:

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Aging and Technology **Diffusion**:

- In customer-facing industries, users may have preferences over the technology used;
- Preference for technologies may different across cohort of consumers (old vs. young);
- If businesses internalize their customers' preferences, then aging population may slow down adoption of techs.

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To examine this hypothesis, we focus on the rise of **mobile payments** in **India**.

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 - [B.] Younger consumers are characterized by preference for mobile payments

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Implications from the model:

Age affects the use of the technology both directly and indirectly

Indirect effect: firms facing more young customers adopt mobile payments more

 \implies the diffusion of tech improvements is slower when there are more older customers

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③ Test model implications using a fintech's introduction of mobile payments in 2019

- * Firms' demand for mobile payments reflect the demographic of their clients:
 - ... firms with **younger** customers demand mobile payments significantly **more**

Contribution

(1) (Slow) technology diffusion in absence of frictions

[Hall and Khan (2003); Comin and Hobijn (2010); Foster and Rosenzweig (2010); Manuelli and Seshadri (2014)]

Financial technology adoption: drivers and impacts

[Chodorow-Reich et al. (2019); Hu et al. (2019); Aggarwal et al. (2023); Crouzet et al. (2023); Dubey and Purnanandam (2023); Alok et al. (2024); Higgins (2024); Sarkisyan (2024); Vallee et al. (2024)]

3 Productivity implications of large demographic transitions

[Feyrer (2007, 2008); Acemoglu and Restrepo (2017,2022); Maestas et al. (2023); Derrien et al. (2023)]

- * Consumers' preference an important factor explaining the diffusion of new technologies:
 - ... service sector vs. manufacturing
 - ... multi-homing

Roadmap

1) Background: Mobile Payments in India

- Age and Mobile Preferences
- ③ Model
- ④ Firm's Adoption and Demographics
- (5) Conclusion

1. Background: Mobile Payments in India

Electronic Payments in India

Phase 1: Traditional Cards

- India had all major players in the card space;
- In 2015, cards' volume were >90% of electronic payments.

Electronic Payments in India

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Phase 2: Mobile Payments \Rightarrow Mobile Wallets

- Preload payment method using a digital device;
- Became very popular after the Demonetization in 2016 [Chodorow-Reich et al. 2019; Crouzet et al. 2023]

Electronic Payments in India

Phase 1: Traditional Cards

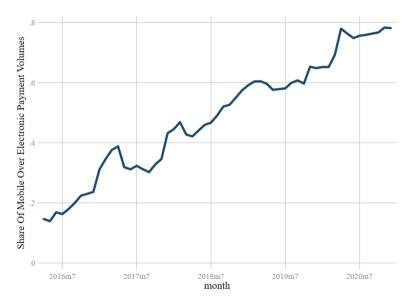
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Phase 2: Mobile Payments \Rightarrow Mobile Wallets

- Preload payment method using a digital device;
- Became very popular after the Demonetization in 2016 [Chodorow-Reich et al. 2019; Crouzet et al. 2023]

Phase 3: Mobile Payments \Rightarrow Unified Payment Interface (UPI)

- Real time bank-to-bank transfer, and interoperability;
- Introduced in 2016, but took off after 2017.



① Mobile payment has lower adoption cost than cards;

2) For merchants, mobile payments has usually lower fees;

- Consumers normally do not pay fees either ways.
- Different customer experience;
 - Physical card vs. QR code.
 - Digital Integration through payment app.

- India experienced an impressive shift from card to mobile payments.
- This is striking, in particular compared to how prevalent are cards in other countries:
 - Europe and US are still mostly card-centric.
 - In 2023, ApplePay only accounted for 3.1% of in-store transactions in US [CapitalOne Research]

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 - Europe and US are still mostly card-centric.
 - In 2023, ApplePay only accounted for 3.1% of in-store transactions in US [CapitalOne Research]
- Could demographic differences explain some of these differences?
 - Hard to examine this question with cross-country data.
 - Test the underlying mechanism using Indian Data

2. Age and Mobile Payments

Measuring the use of mobile payments

- Use data from one of the top four bank in India [Agarwal et al., 2023]
- Full account info on about 200,000 customers
 - age distribution close to representative survey of Indian households (head)
 - have wealthier individuals than the typical Indian household

(period: Jan-Feb 2020)

Figure

Figure

Measuring the use of mobile payments

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- Full account info on about 200,000 customers
 - age distribution close to representative survey of Indian households (head)
 - have wealthier individuals than the typical Indian household
- In this data, we can measure:
 - 1 Individual Age
 - (2) Share of mobile Payments over total electronic payments

(period: Jan-Feb 2020)

Figure

- Does age explain the relative use of mobile vs. cards?
- How much of the variance in behavior is explained by age vs. other demographic variable?
- Shapley R-squared decomposition method [Huettner and Sunder 2012; Israeli 2007]

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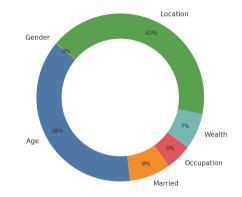


FIGURE 1: Mobile Share: Variance Decomposition

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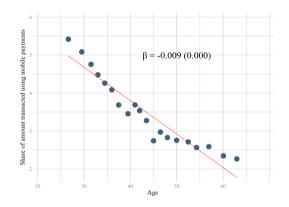


FIGURE 2: Mobile vs. Cards

- Does age explain the relative use of mobile vs. cards?
 - Yes! Age explains as much variance as location (i.e., pincode).
- Are younger individuals using mobile relatively more?
 - Yes! The use of mobile by the oldest group is about half than the youngest group.
- Potential confounding: Controls
 - Younger people are different (e.g., poorer) than older people.

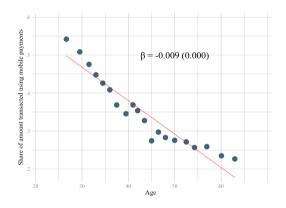
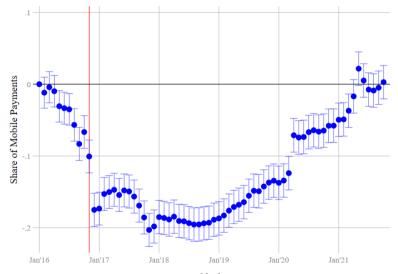


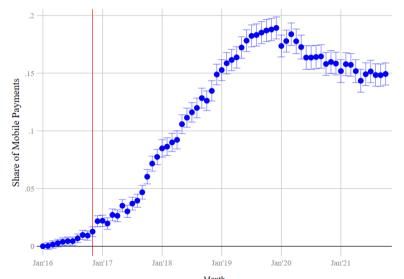
FIGURE 3: Mobile vs. Cards

Difference in Mobile Payments Penetration Among Early Card Users vs. Not



Notes: Month-by-month difference in the share of mobile transactions among early card users vs no card users using bank panel data 13 / 36

Growth in Mobile Payments: Young vs. Old



Notes: Month-by-month difference in the share of mobile transactions between young and old consumers using bank panel data

Taking stock: Mobile Payments and Age

- Does age explain the relative use of mobile vs. cards?
 - Yes! Age explains as much variance as location (i.e., pincode)
- Are younger individuals using mobile relatively more?
 - Yes! The use of mobile by the oldest group is about half than the youngest group
 - Hard to rationalize by differences in observable
- Younger adults generally prefer mobile to traditional cards

3. Model

Key elements

Businesses j = 1, ..., J

a(*j*): investment in technology [e.g., offering mobile payment]

Consumers $i \in [0, 1]$

Each *i* chooses which business *j* to make purchases from. Surplus from transacting with business *j* can depend on *a*(*j*) [e.g., young consumers enjoy mobile payments]

Static, partial equilibrium (wage *w* fixed)

Consumer problem

$$\max_{j, c(i,j)} \quad \frac{\log(c(i,j))}{\nu - 1} + \epsilon(i,j)$$

s.t. $p(j)c(i,j) \le w$

• $\varepsilon(i, j)$: taste shifters

$$i \in \text{Old}$$
 : $\varepsilon(i,j) \sim \exp\left(-\exp(-z)\right)$
 $i \in \text{Young}$: $\varepsilon(i,j) \sim \exp\left(-\exp(-z - \log(a(j)))\right)$

• $a(j) \uparrow \implies$ first-order stochastic shift in $\varepsilon(i,j)$

Consumer demand

$$\frac{\equiv s_{Y}(p(j), a(j))}{\% \text{ young consumers picking } j} = \frac{a(j)}{J} \left(\frac{p(j)}{P_{Y}}\right)^{-\frac{1}{\nu-1}}$$

$$P_{Y} \equiv \left(\frac{1}{J} \sum_{j=1}^{J} a(j)p(j)^{-\frac{1}{\nu-1}}\right)^{-(\nu-1)}$$

$$\underbrace{\equiv s_{O}(p(j))}{\% \text{ old consumers picking } j} = \frac{1}{J} \left(\frac{p(j)}{P_{O}}\right)^{-\frac{1}{\nu-1}}$$

$$P_{O} \equiv \left(\frac{1}{J} \sum_{j=1}^{J} p(j)^{-\frac{1}{\nu-1}}\right)^{-(\nu-1)}$$

Only young consumers' preferences are sensitive to technology choices.

Businesses (1/2)

Total demand for business *j*:

$$D(j) = \theta s_{Y}(p(j), a(j)) \frac{w}{p(j)} + (1 - \theta) S_{O}(p(j)) \frac{w}{p(j)}$$

$$\theta = \text{fraction of young in population}$$

Production costs = w D(j)marginal cost = w

Technology adoption costs = w c(a(j)) [c(0) > 0, c' > 0, c'' > 0] marginal cost = wc'(a(j))could capture cost of workforce training; uncertainty about profitability

Businesses (2/2)

$$p(j) = \nu w$$

$$c'(a(j)) = \frac{\theta}{J} \left(\frac{p(j)}{P_Y}\right)^{-\frac{1}{\nu-1}} \left(1 - \frac{w}{p(j)}\right)$$

Young and old have the same price elasticity of demand \implies markup = ν

For an <u>individual</u> firm, increasing a(j) raises market share of young.

On which they earn a markup

Symmetric businesses
$$\implies ac'(a) = \frac{\theta}{J} \left(1 - \frac{1}{\nu}\right)$$

Key predictions

P1: Technology adoption by businesses increases with the young share:

$$\frac{da}{d\theta} > 0.$$

[Even if in equilibrium, their efforts cancel out.]

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Assume:
$$c(a) = \frac{\gamma}{2} (a-1)^2$$
.

P2: A higher young share magnifies the effects of changes in adoption costs $[\gamma]$

$$\frac{da}{d\gamma} < 0, \quad \frac{d^2a}{d\theta d\gamma} < 0.$$

[We don't need that particular functional form.]

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Setting:

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- We study the demand for service provided by an important fintech payment Company.
- Up to 2019, the company only sold traditional point-of-sales (POS) machines.
- In May 2019, the Company introduced mobile payment option (QR-code) as an additional service.

Test: We compare how overall adoption for our Company's services:

- (A) After vs. Before May 2019: with vs. without mobile payment option
- (B) Across districts with different age composition

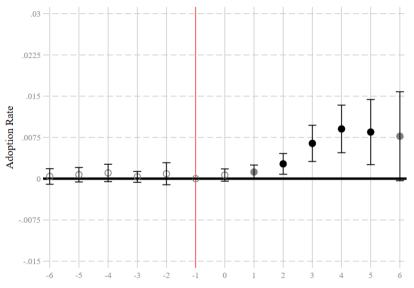
Empirical Framework

Differences-in-differences framework:

$$AdoptionRate_{d,t} = \alpha_d + \alpha_t + \sum_{k=-6, k\neq -1}^{k=+6} \beta_k \left(Young_d \times 1_{\{t=t_0+k\}} \right) + \Gamma'_t \mathbf{X}_d + \epsilon_{dt}.$$

where:

- $AdoptionRate_{d,t} = \frac{\text{number of stores joining the platform in district } d \text{ and month } t}{\# \text{ of firms (in 100s) in the district (Census)}}$
- *Young_d* : share of adults that are less than 30 years old (more later);
- **X**_d: district-level characteristics (more later);
- We focus on a 6-month window before and after $t_0 = May 2019$

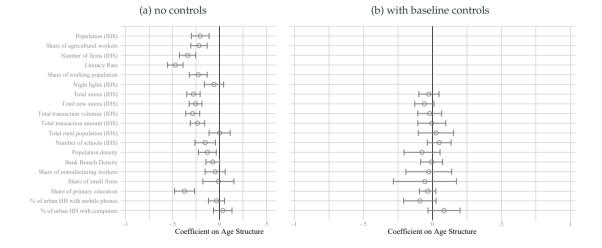


Month relative to the shock

- After the introduction of mobile payments, the adoption increased relatively more in areas with a younger population
- This effect is sizable: 1 s.d. increase in the share of young adult $\Rightarrow \approx 25\%$ increase relative to the baseline adoption rate
- Main concerns:

① areas with a younger population are different?

Age Structure and District characteristics

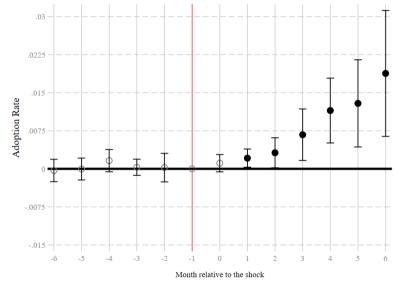


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[OLS with district controls \times month f.e.]

(1) Demographics and Mobile Adoption: with baseline controls x month f.e.



baseline controls: population; share of agri. workers; number of firms; literacy rate; share of working pop.; nightlight intensity

Robustness 27 / 36

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(2) *local dynamism* : young people \implies moving in more dynamic areas

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 local dynamism : young people ⇒ moving in more dynamic areas [IV-2SLS approach]

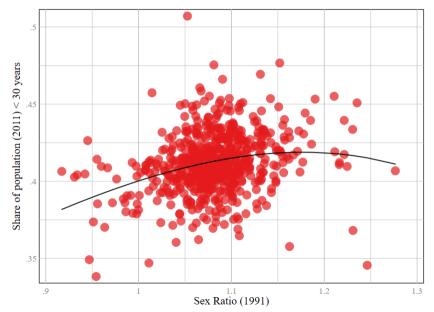
(2) Demographics and Mobile Adoption: an IV-2SLS approach

- We exploit historical determinants of fertility as an instrument for the share of young people
- Idea: areas with higher expected fertility in early 1990s \rightarrow larger share of younger population in late 2010s
 - \star variation orthogonal to recent migration trends

(2) Demographics and Mobile Adoption: an IV-2SLS approach

- We exploit historical determinants of fertility as an instrument for the share of young people
- Idea: areas with higher expected fertility in early 1990s \rightarrow larger share of younger population in late 2010s
 - \star variation orthogonal to recent migration trends
- District-Level Sex Ratio in 1990: a skewed sex ratio should affect the marriage market and consequently fertility [Guilmoto 2012; Dyson 2012; Angrist 2000]

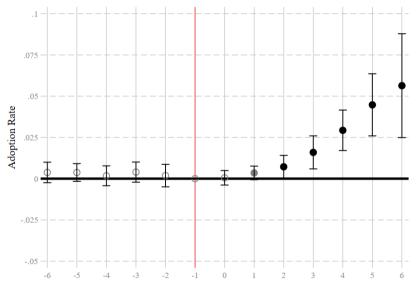
(2) Correlation: Sex Ratio_{*d*,1991} and Age Structure_{*d*,2011}



| | First Stage | 2SLS | | |
|--|--|-------------------------|-----------------------------|--|
| | $\overline{ AgeStructure_d} \\ \times Post_t \\ (1)$ | Adoption rate (2) | # Adoptions (IHS) (3) | |
| | | | | |
| $(\text{Sex Ratio})_{d,1991} \times \text{Post}_t$ | 61.04*** (11.71) | | | |
| $(\text{Sex Ratio})^2_{d,1991} \times \text{Post}_t$ | -25.70*** (5.332) | | | |
| $AgeStructure_d \times Post_t$ | | 0.020*** | 0.256*** | |
| | | (0.0046) | (0.085) | |
| Observations | 7,722 | 7,722 | 7,722 | |
| SW F-statistic | 43.46 | | | |
| District f.e. | \checkmark | \checkmark | \checkmark | |
| Month f.e. | \checkmark | \checkmark | \checkmark | |
| Controls \times Month f.e. | \checkmark | \checkmark | \checkmark | |

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③ other district-level confounders

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(3) other district-level confounders [within-district comparison in areas with and w/o universities]

(3) Demographics and Mobile Adoption: University Analysis

- Within a city, neighborhoods with universities:
 - Should have similar culture, institutions, type of business owners than other neighborhoods.
 - **but** a larger share of customers should be young adults (i.e., students).

(3) Demographics and Mobile Adoption: University Analysis

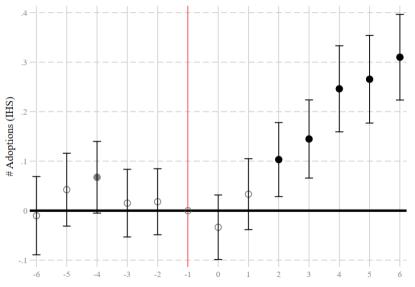
- Within a city, neighborhoods with universities:
 - Should have similar culture, institutions, type of business owners than other neighborhoods.
 - **but** a larger share of customers should be young adults (i.e., students).
- We manually collect the main pincode of operation for all Indian Universities
- Compare adoption across pincodes with and without universities, within the same district:

$$Adoption_{p,t} = \alpha_{dt} + \alpha_p + \sum_{k=-6, k\neq -1}^{k=+6} \gamma_k \left(1\{Univ\}_p \times 1_{\{t=t_0+k\}} \right) + \nu_{pt}$$

where:

 $1{Univ}_p = 1$ if there is university in pincode *p* in district *d*; 0 otherwise

(3) Demographics and Mobile Adoption: University Analysis



Month relative to the shock

(3) University Analysis: Sub-sample results

| | (1) | (2) | (3) | (4) |
|--|--------------------|--------------------|---------|----------|
| 1(has university) _p × Post _t | 0.065*** | 0.076*** | 0.000 | 0.171*** |
| | (3.30) | (3.75) | (0.00) | (6.93) |
| | | Student businesses | | |
| Sample | Student businesses | (expanded) | Placebo | Others |
| Pincode FE | Y | Y | Υ | Y |
| District \times Month FE | Y | Y | Υ | Y |
| Adj R-Sq | 0.674 | 0.693 | 0.310 | 0.628 |
| Obs | 109,626 | 109,626 | 109,626 | 109,626 |

Figures

Taking stock: Demographics and Mobile Payments Diffusion

After the introduction of mobile payments, the adoption increased relatively more in areas with a younger population

.... result consistently using different methodologies and samples

... confirms the prediction of the model: a younger population leads store to more likely adopt new payment technologies

5. Conclusion

Summary and Next Steps

Mobile payments surpassed cards as the leading electronic payment option b/w 2016-20.

Using a model and data to show:

- ① Young adults show a preference for mobile versus cards.
- (2) Firms tend to internalize this preference, fostering more adoption of the new technology where young adults are a sizable share of the customer base.

Evidence suggests that demographic differences may explain the diffusion of new technologies

- an older society can be slower at picking up new technologies
- + similar evidence with Brazil's instant payment system Pix

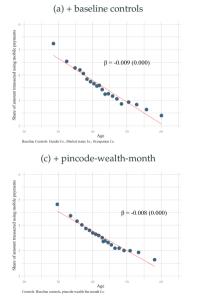
Next steps:

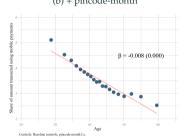
implications of demographics \times strategic complementarities (in network-based technologies) for technology adoption and diffusion

Figure

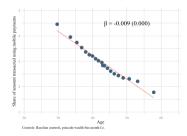
Appendix

Mobile vs. Cards: with controls



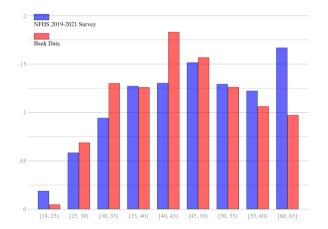


(d) conditional on holding a credit card



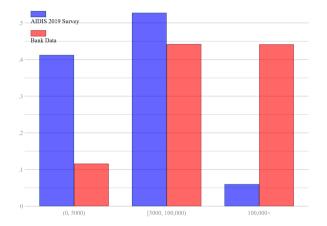
(b) + pincode-month

Age Comparison, Bank data



Bank sample compared to data from the National Family Health Survey (NFHS) from 2019-2021.

Deposit Amount Comparison, Bank data



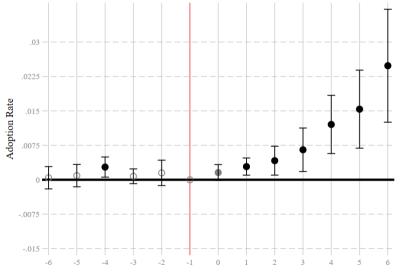
Bank sample compared to data from the AIDIS (2019).

Basic robustness tests

- 1 Alternative "young" definition (i.e., 40 years);
- 2 Alternative reference population (i.e., full);
- 3 Use log-transformed (IHS) outcome;
- 4 Scale outcome by population;
- 5 Focus on all outcomes in the platform;

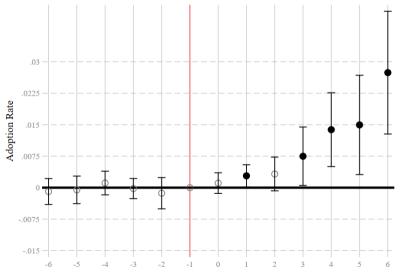


Robustness: Young as less than 40yr.



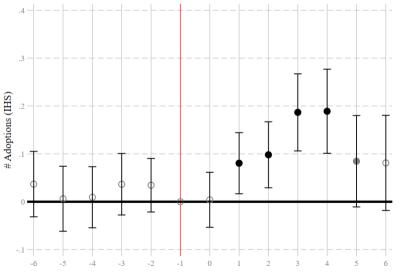
Month relative to the shock

Robustness: treatment based on the full population



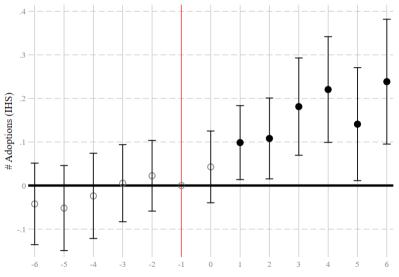
Month relative to the shock

Robustness: IHS specification (w/o contr.)

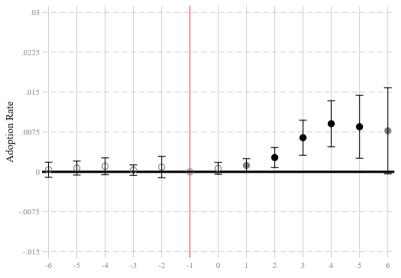


Month relative to the shock

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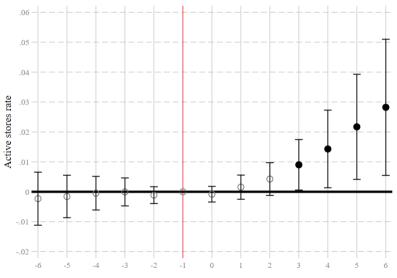


Robustness: outcome scaled by population

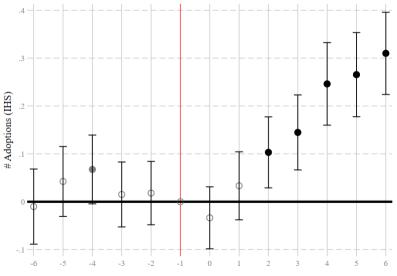


Month relative to the shock

Robustness: total stores in the platform

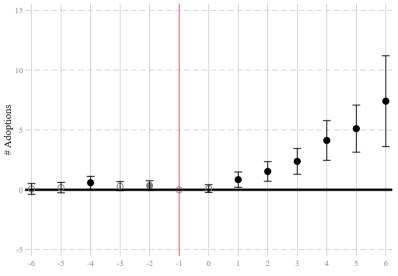


University Analysis: only University districts



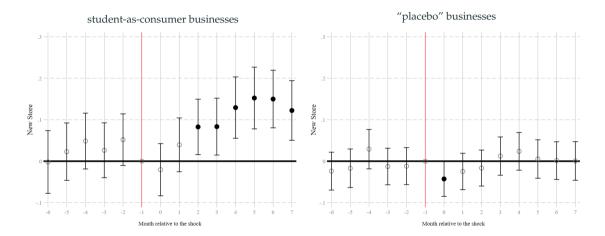
Month relative to the shock

University Analysis: in level (no adj.)



Month relative to the shock

(3) University Analysis: Sub-sample results



Similar Evidence From Brazil

