On the Rise of Payment Firms

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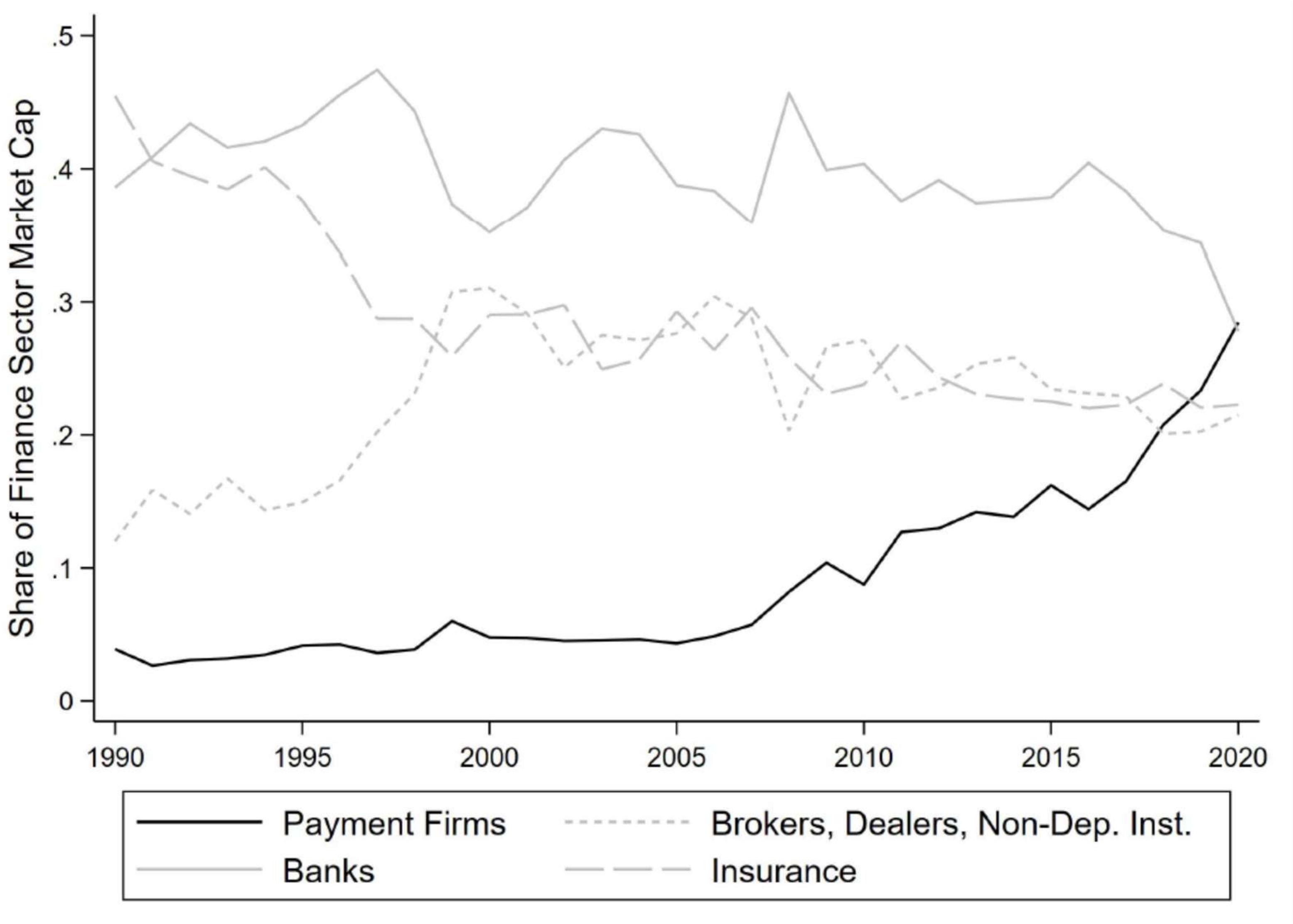
Motivation



Share of Finance Sector Market Cap
.5
.4
.3
.2
.1
0
1990
1995
2000
2005
2010
2015
2020
Payment Firms
Banks
Brokers, Dealers, Non-Dep. Inst.
Insurance

Motivation

- Rise of payment firms: one of the most significant changes to financial industry in the last decade

- This paper:
  - Document the rise of payment firms
  - Provide evidence of importance of payment firms for E-Commerce sales, using 3mn observations from E-Commerce firm

- Key findings:
  - E-Commerce drives rise in payment firms
  - Clientele effect: ~1/4 of customers abandon purchase when their prefered payment method is not available / not easy to use
  - Documented for Buy-Now-Pay-Later, Credit Card, Paypal

Outline

1. Descriptive statistics on the rise of payment firms

2. Link rise in E-Commerce to rise in payment firms

3. Micro evidence on the importance of payment firms for E-Commerce sales

Data

- Listed firms located in the U.S. with SIC codes
  - 60 (Banks)
  - 61/62 (Brokers, Dealers, Non-depository Institutions)
  - 63/64 (Insurance) and
  - Payment firms

- Classification of payment firms
  - SIC codes 6099 (Functions related to Depository Banking), 6141 (Personal Credit Institutions), or SIC code that does not start with 6
  - AND: contains word “payment” or “merchant solution”

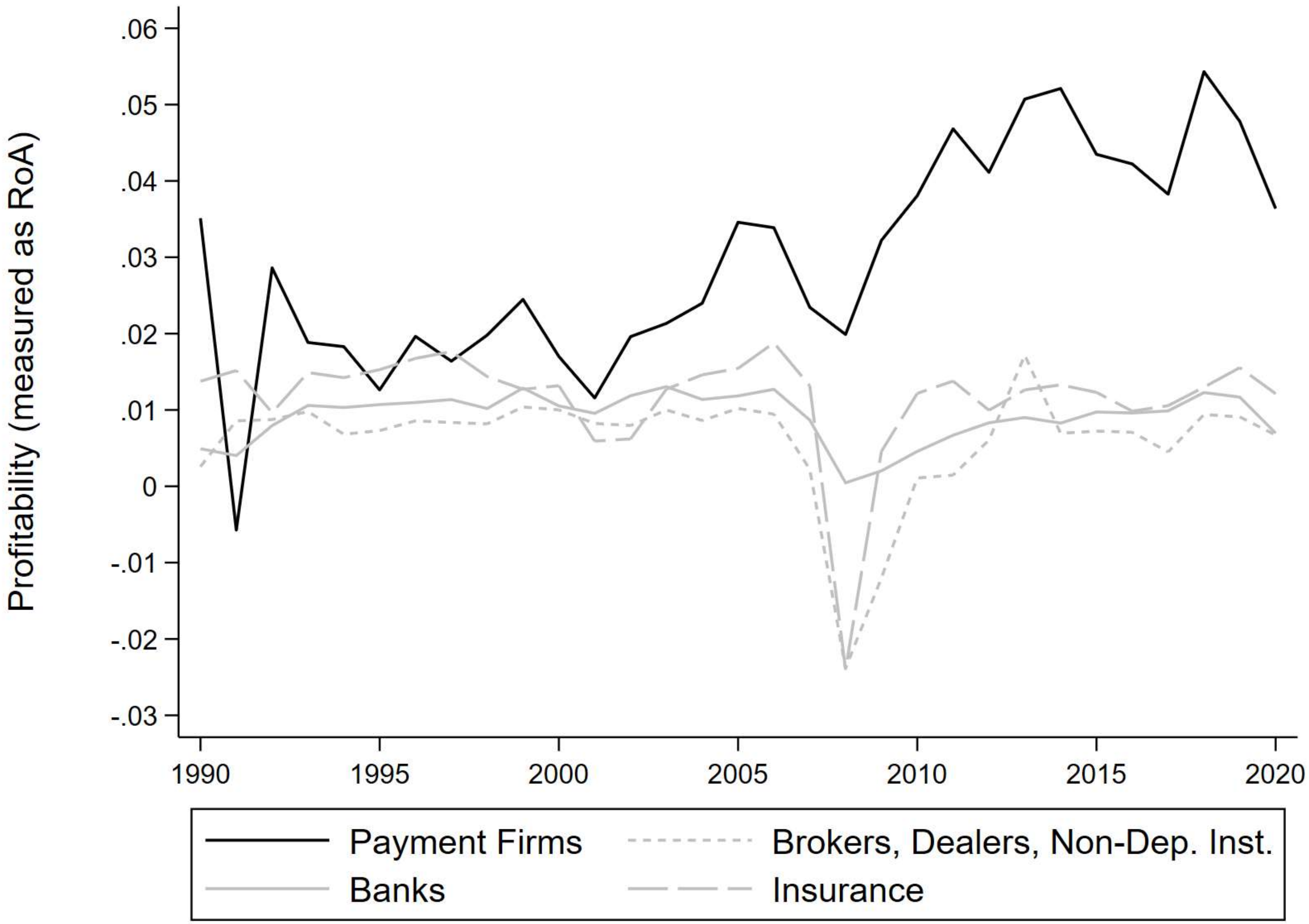
- Cross-checked with Nilson Reports

- 1990-2020. Market Capitalization = prcc_c · csho via Compustat

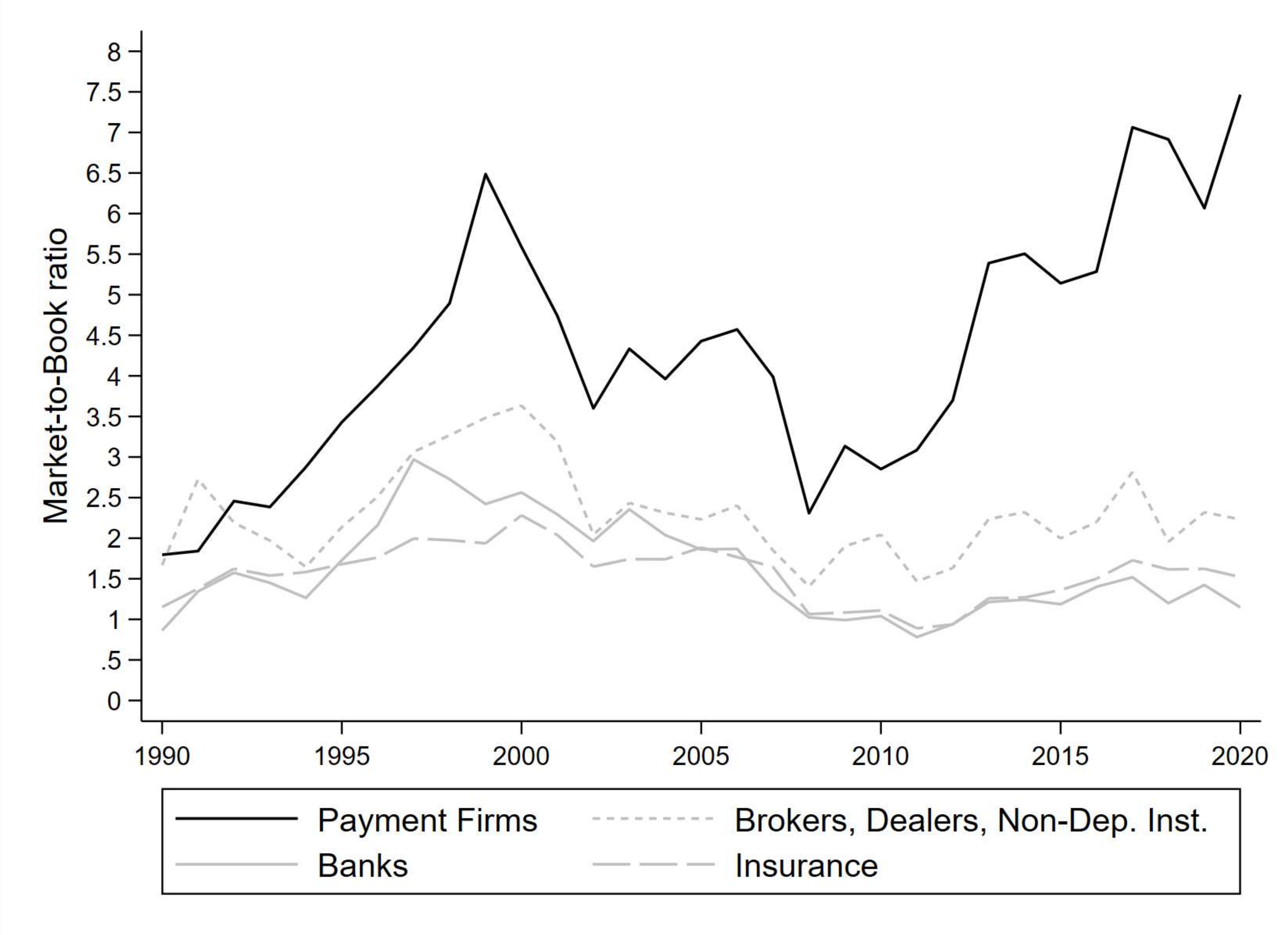
Largest 10 financial firms by subsector in 2020

Rank	Payment Firms	Banks	Brokers, Dealers, Non-Dep. Institutions	Insurance
1	Visa (465bn)	JP Morgan (387bn)	Morgan Stanley (124bn)	United Health (332bn)
2	Mastercard (355bn)	Bank of America (262bn)	Blackrock (110bn)	Anthem (79bn)
3	PayPal (275bn)	Citigroup (128bn)	Charles Schwab (100bn)	Cigna (74bn)
4	Square (99bn)	Wells Fargo (125bn)	Goldman (95bn)	Marsh & McLennan (59bn)
5	American Express (97bn)	US Bancorp (70bn)	CME (65bn)	Progressive Corp (58bn)
6	FIS (88bn)	Truist (65bn)	ICE (65bn)	Humana (53bn)
7	Fiserv (76bn)	PNC (63bn)	Capital One (45bn)	Metlife (42bn)
8	Global Payments (64bn)	BNYM (38bn)	Blackstone (44bn)	Travelers (35bn)
9	Discover (28bn)	State Street (26bn)	MSCI (37bn)	Centene (35bn)
10	Fleetcor (23bn)	First Republic (26bn)	T. Rowe Price (35bn)	Verisk (34bn)

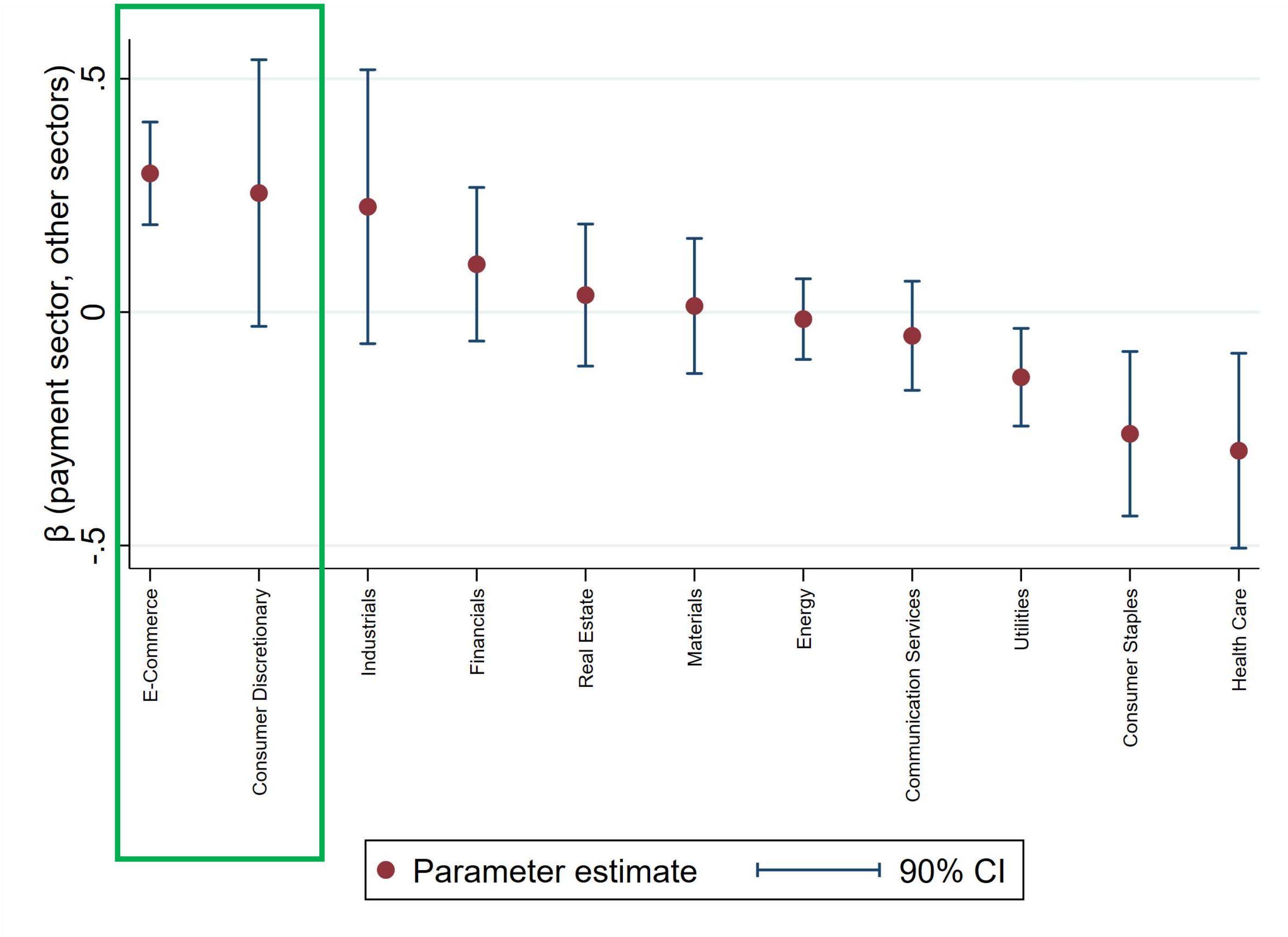
Profitability of payment firms



Market-to-book of payment firms

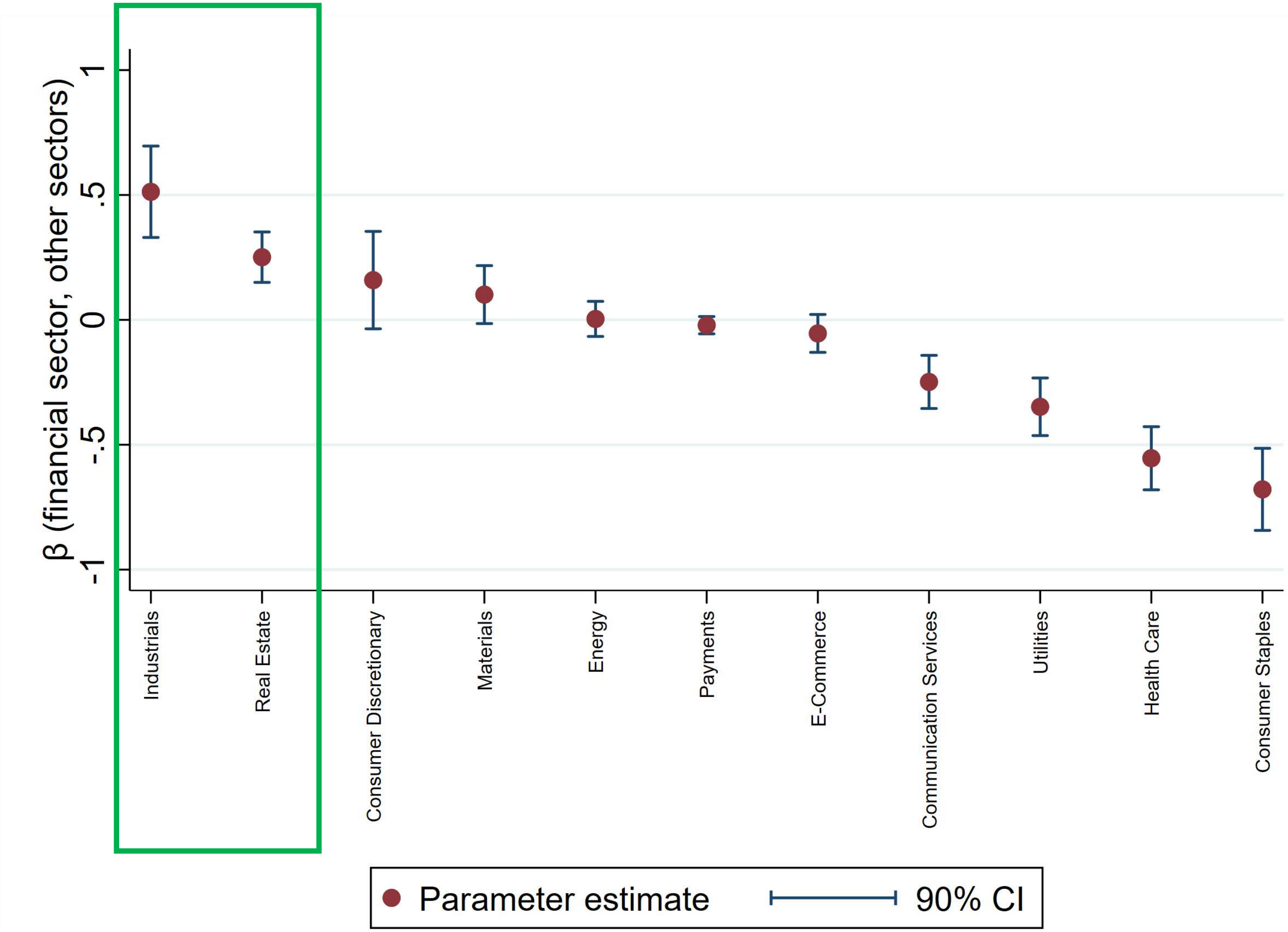


E-Commerce↑ = Payment Firms↑



The figure depicts coefficient β of regressions of the form $y = \alpha + \beta x$, where x are weekly stock index excess returns of the main economic sectors and y is the weekly excess stock returns of payment firms. The sample period is from 2004-2021.

Industrials/Real Estate↑ = Financials↑



The figure depicts coefficient β of regressions of the form $y = \alpha + \beta x$, where x are weekly stock index excess returns of the main economic sectors and y is the weekly excess stock returns of financial firms (ex payment firms). The sample period is from 2004-2021.

E-Commerce-minus-BrickAndMortar factor

Payment firms: Fama-MacBeth regression (1st stage)

Panel A: Payment sector

	(1)	(2)	(3)	(4)	(5)
	2004-2021	2004-2021	exclude 2008/2009	exclude 2020/2021	Refined Brick-and-Mortar
E-Commerce minus Brick-and-Mortar (EMB)		0.244***	0.157***	0.247***	0.162***
		(4.255)	(2.761)	(4.298)	(2.821)
Market	1.136***	1.075***	1.038***	1.081***	1.099***
	(19.66)	(18.75)	(17.52)	(17.37)	(18.82)
SMB	-0.0775	-0.144	-0.127	-0.165*	-0.0951
	(-0.750)	(-1.428)	(-1.239)	(-1.665)	(-0.934)
HML	-0.0550	0.00431	-0.0564	-0.0164	-0.00997
	(-0.590)	(0.0476)	(-0.603)	(-0.164)	(-0.107)
RMW	-0.0221	0.206	0.0683	0.351**	0.143
	(-0.168)	(1.502)	(0.487)	(2.286)	(1.007)
CMA	-0.349**	-0.142	-0.286*	-0.0133	-0.226
	(-2.130)	(-0.862)	(-1.769)	(-0.0775)	(-1.350)
Constant	0.275	0.145	0.163	0.255	0.185
	(1.200)	(0.651)	(0.764)	(1.198)	(0.814)
Observations	216	216	192	192	216
Adj R^2	0.695	0.718	0.688	0.729	0.705

E-Commerce-minus-BrickAndMortar factor

Financial firms: Fama-MacBeth regression (1st stage)

Panel B: Financials (ex-Payment-Sector)

	(1)	(2)	(3)	(4)	(5)
	2004-2020	2004-2020	exclude 2008/2009	exclude 2020/2021	Refined Brick-and-Mortar
E-Commerce minus Brick-and-Mortar (EMB)		-0.0733**	-0.0628**	-0.0678	-0.105***
		(-1.980)	(-2.023)	(-1.622)	(-2.930)
Market	1.159***	1.177***	1.103***	1.189***	1.184***
	(32.08)	(31.79)	(34.05)	(26.22)	(32.47)
SMB	-0.369***	-0.349***	-0.236***	-0.342***	-0.357***
	(-5.708)	(-5.373)	(-4.214)	(-4.748)	(-5.619)
HML	1.076***	1.058***	0.837***	1.125***	1.047***
	(18.48)	(18.08)	(16.36)	(15.44)	(18.03)
RMW	-0.542***	-0.611***	-0.492***	-0.573***	-0.649***
	(-6.594)	(-6.886)	(-6.418)	(-5.126)	(-7.324)
CMA	-0.545***	-0.607***	-0.459***	-0.642***	-0.625***
	(-5.318)	(-5.700)	(-5.203)	(-5.130)	(-5.992)
Constant	-0.313**	-0.274*	-0.173	-0.340**	-0.255*
	(-2.186)	(-1.908)	(-1.479)	(-2.189)	(-1.795)
Observations	216	216	192	192	216
Adj R^2	0.906	0.907	0.908	0.897	0.909

Micro Evidence

German E-commerce company selling furniture

- 3mn observations

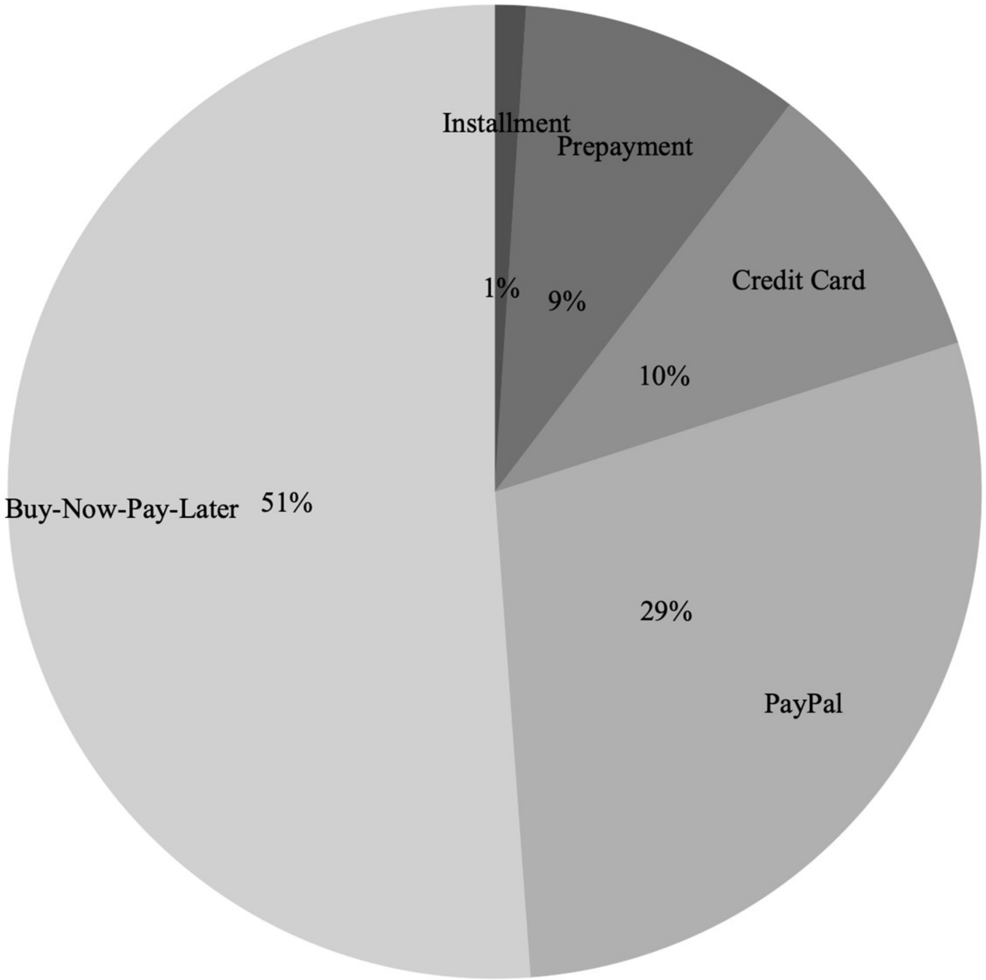
Setting:

- 1. Customer proceeds with items to check-out & enters information
- 2. Retailer offers payment options
- 3. Customer selects payment option
- 4. Retailer decides about additional verification (if Credit Card is used)
- 5. Customer purchases ("conversion")

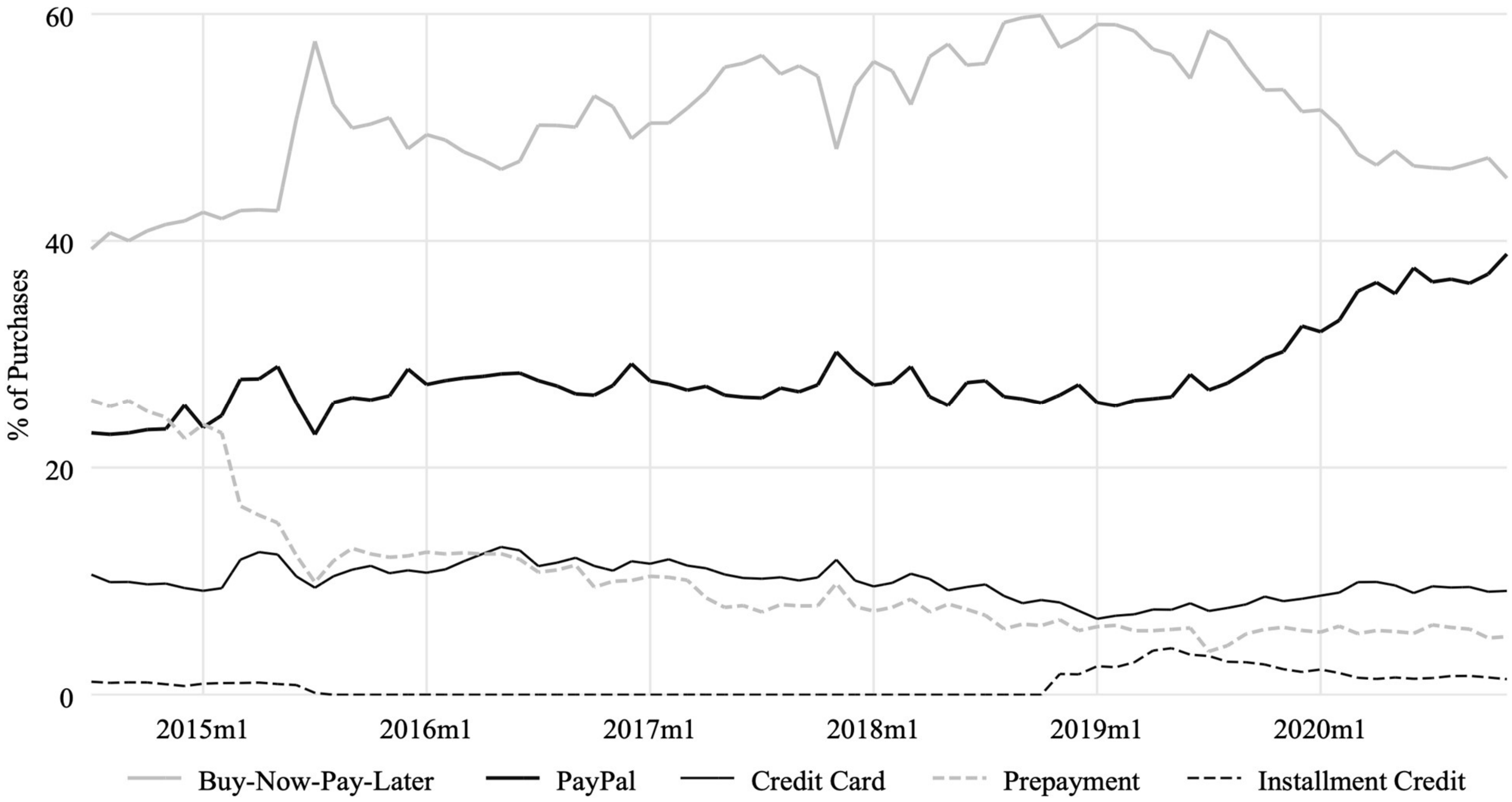
Do customers "stick" to preferred payment methods? → Clientele Effect?

Or do they switch to easily available low-cost alternatives?

Payments Used at the Retailer



Payments Used at the Retailer



Order of analysis

We analyze three payment types

1. Credit cards
2. PayPal
3. BNPL

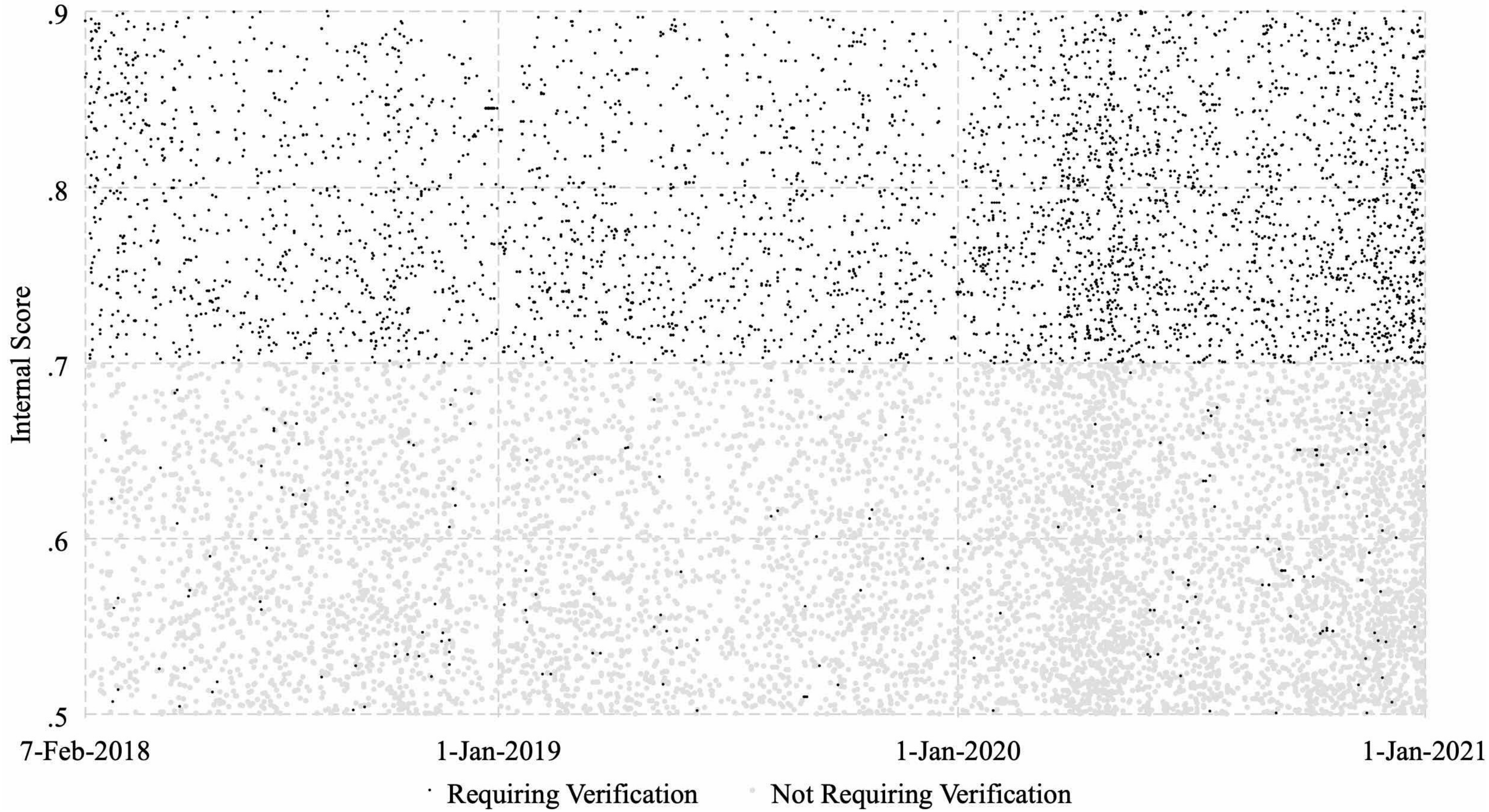
For each of the three types, we have an (exogenous) shock to the availability / ease of use of that particular payment type

Credit cards and BNPL: RDD design

PayPal: IV design

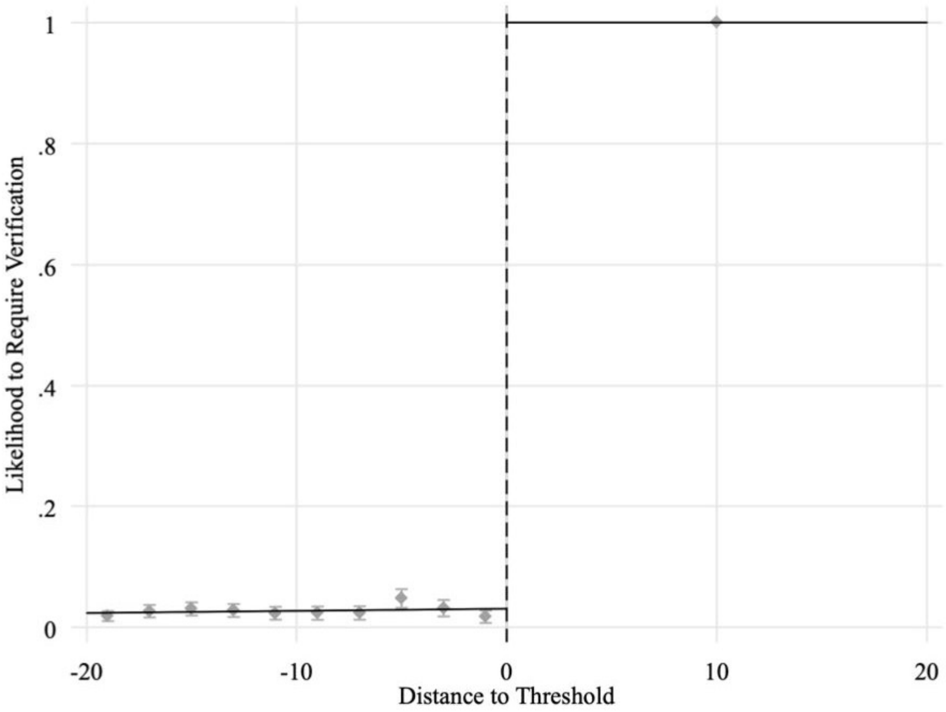
Credit Card: Additional Verification Requirment

- Internal transaction risk score (higher score = higher fraud risk)
- Customers above 0.7: additional identity verification check (e.g. PIN)
- Customers below 0.7: no check

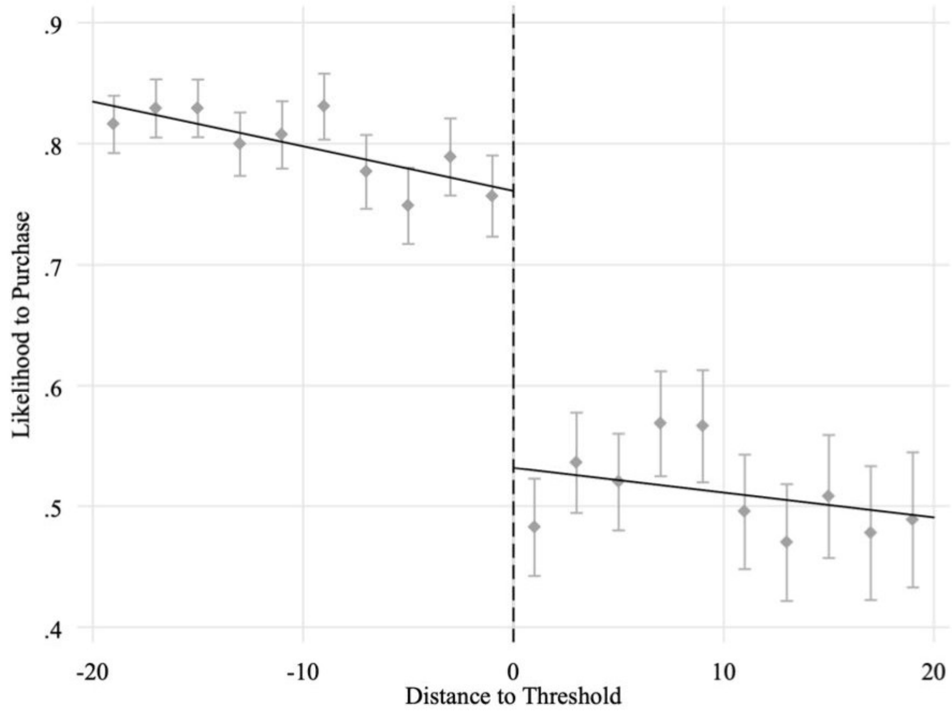


Credit Card: Discontinuity at the Threshold

- Suited for a slightly fuzzy RDD
- Verification check jumps from around 4% to 100%
- Conversion rate drops from 76% to 54%



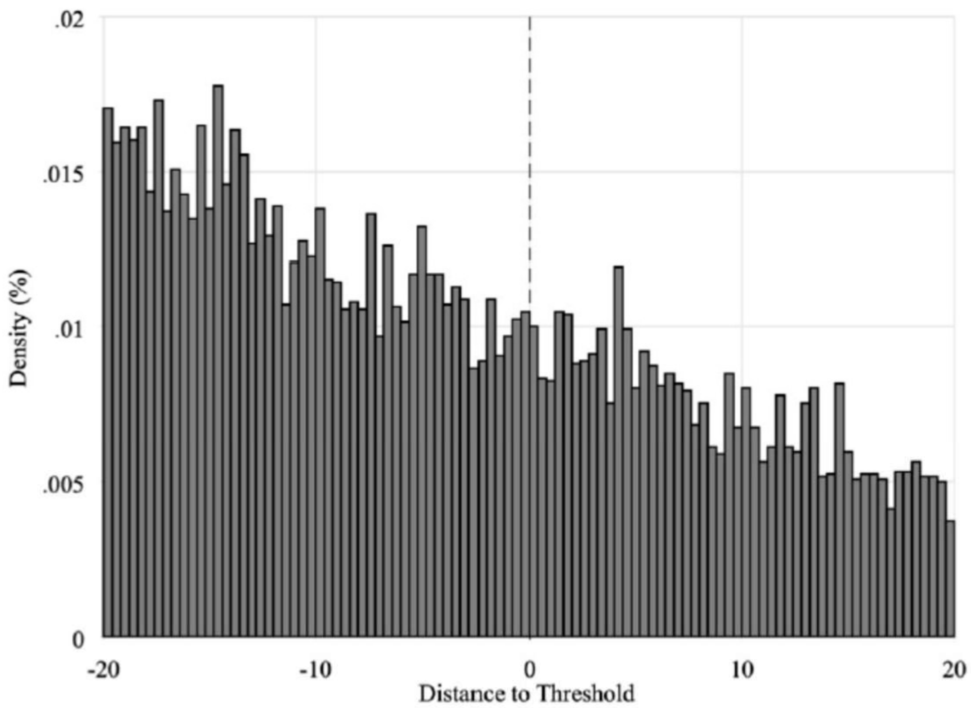
(A) Probability to Require Verification Check



(B) Probability of a Successful Conversion

Credit Card: No manipulation of score

- Customers typically not aware of existence of transaction risk score
- Even if they are, they don't know exact method for calculating score



(c) Histogram of Forcing Variable

fitted values from regressions on either side of the discontinuity.

Credit Card: Estimation

We exploit discontinuities for a fuzzy RDD to estimate a LATE for customers with credit scores around the verification threshold via 2SLS

$$T_{i,t} = \alpha_1 \underline{S}_{i,t} + \alpha_2 S_{i,t} + \alpha_3 \underline{S}_{i,t} \times S_{i,t} + \alpha 4 X_{i,t} + \eta_w + \sigma_c + \varepsilon_{i,t} \qquad (1)$$

$$Y_{i,t} = \beta T^{i,t} + \delta_1 S_{i,t} + \delta_2 \underline{S}_{i,t} \times S_{i,t} + \delta_3 X_{i,t} + \eta_w + \sigma_c + \mu_{i,t} \qquad (2)$$

1. First stage
   - $T_{i,t}$: Likelihood that retailers requires verification
   - $\underline{S}$: indicator for the score being above threshold or below
   - S : score-point distance to the threshold

2. Second stage
   - $Y_{i,t}$: Purchase (yes/no)
   - $T^{i,j}$: Predicted treatment dummy from (1)

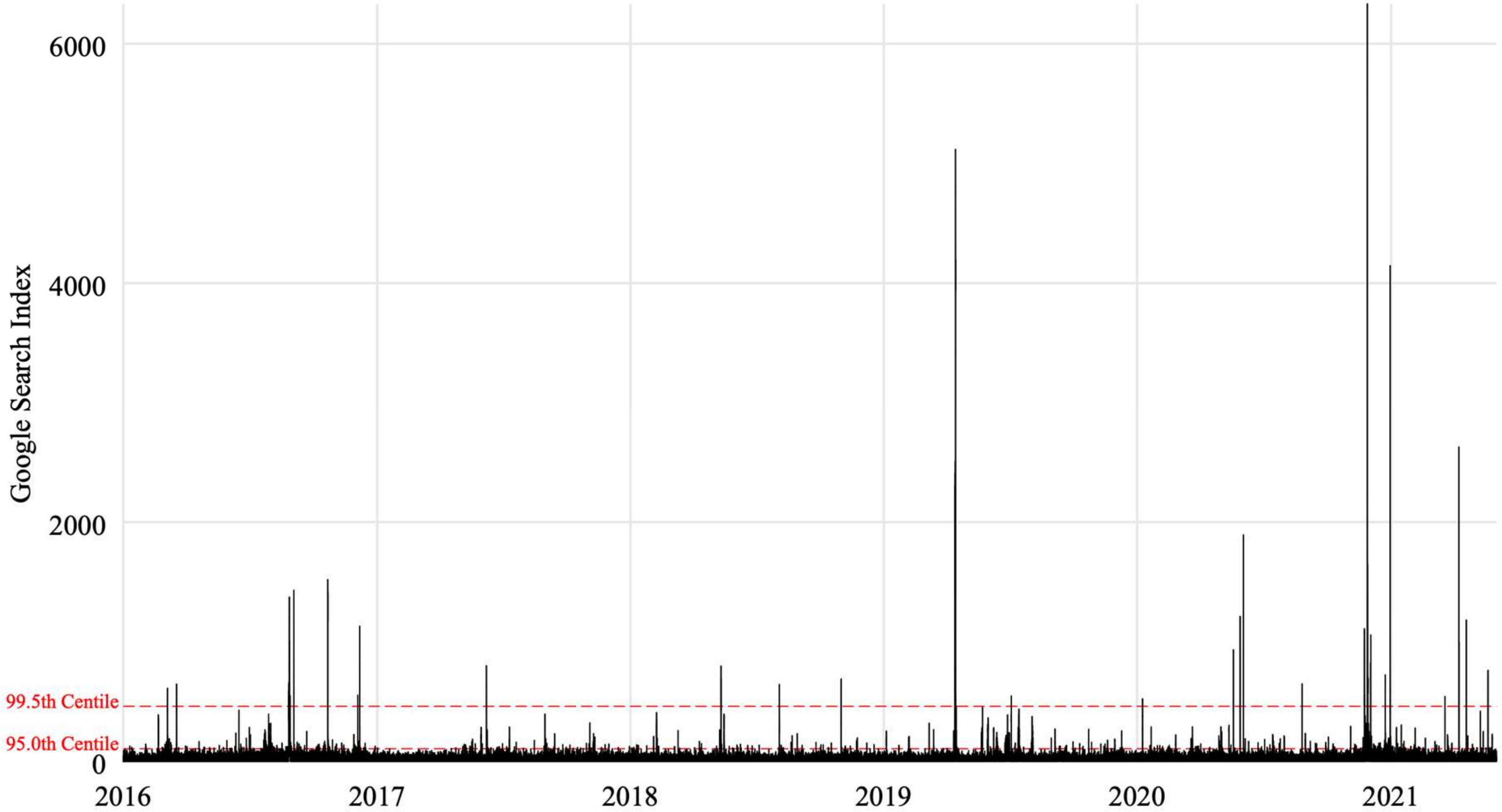
Credit Card: Results

- Recall: 10 / 100 customers choose Credit Card
- 24.8%-25.7% of those abort purchases (=2-3 of the 100 customers)
- Reducing sales by 2.5%

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
Requiring Verification (1/0)	-0.248***	-0.250***	-0.257***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	25,258	22,405	27,309
Observations	14,477	14,474	14,446

PayPal: Outages

- Outages at PayPal are rare but do occur
- We use a Google search index for problems using PayPal in Germany
- Extremely high values (>99.5 percentile) = "PayPal Outage" (1)
- Normal values (<95 percentile) = normal times (0)



PayPal: Estimation

- Effect of an outage on all customers estimated via

$$Y_{i,t} = \beta Z_h + \delta X_{i,t} + \eta_w + \sigma_c + \mu_{i,t} \tag{3}$$

- Z_h : PayPal outage dummy variable (1: outage, 0: no outage)
- $Y_{i,t}$: Conversion dummy (1: purchase, 0: abortion)

Important:

- Google search-based proxy is noisy („1“ does not imply that all customers are affected by the outage during the entire time)
- Payment via PayPal decreases by approximately 10% during PayPal outages
- Identification less ideal than for BNPL and credit card (we do not know the underlying drivers of Paypal outages)

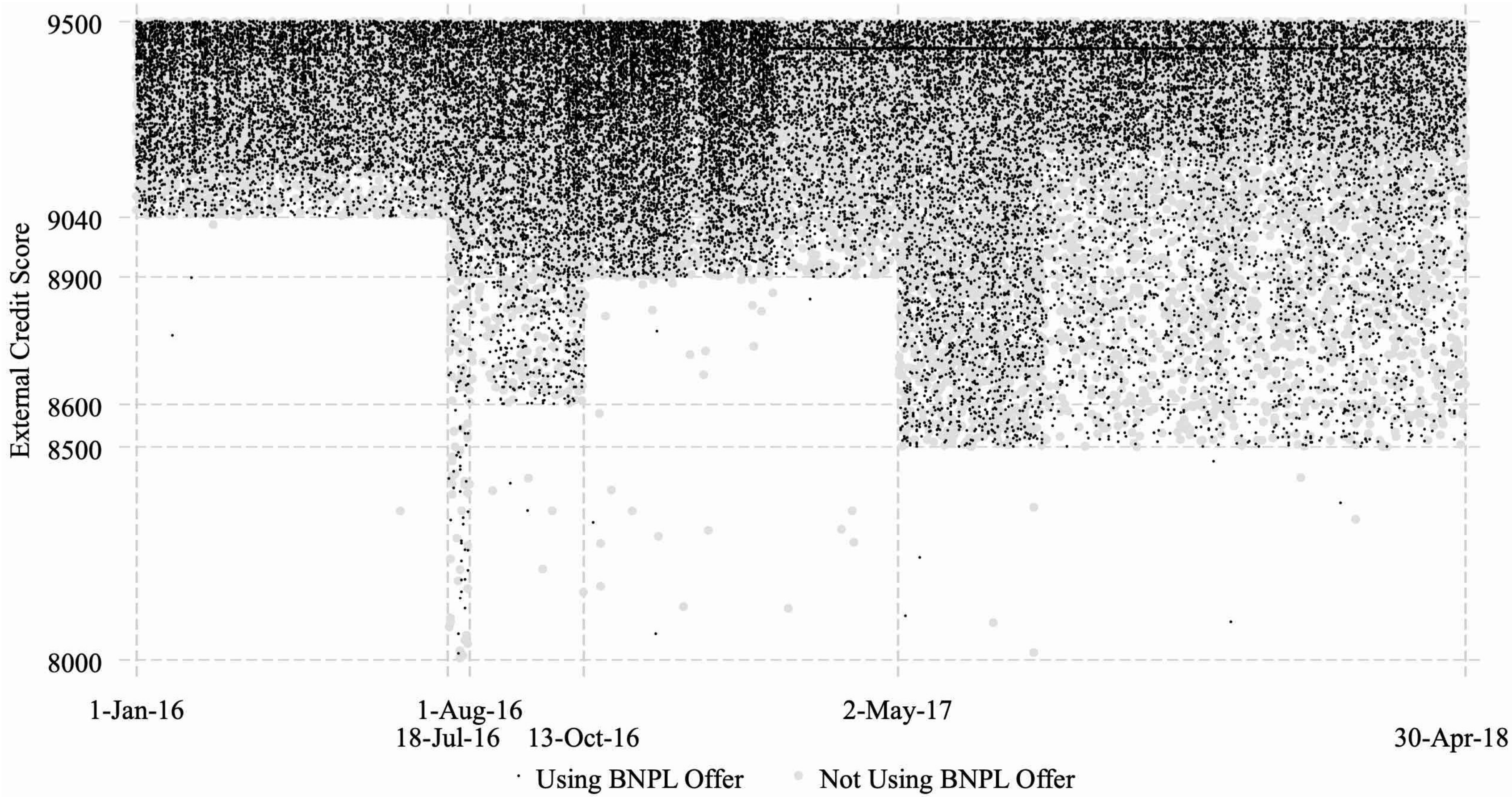
PayPal: Results

- 3.3% of ALL customers abort the purchase
- Recall: 30 / 100 customers choose PayPal
- 3.3 / 30 that typically use PayPal abort (or ~10%)
- Not all PayPal customer affected by outage → conservative estimation >20% of those whose are affected abort the transaction

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
PayPal Outage (1/0)	-0.061***	-0.046***	-0.033***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Observations	2,818,650	2,818,644	2,803,265

Buy-Now-Pay-Later: Creditworthiness cutoff

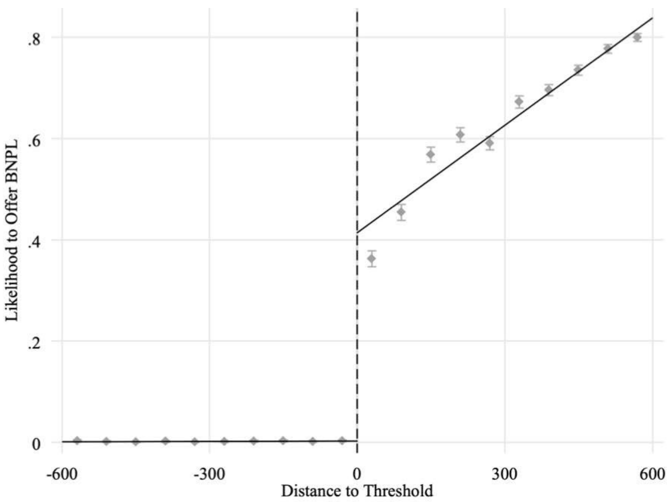
- Credit score (higher score = lower default risk)
- Customers above threshold: most are offered BNPL
- Customers below threshold: most are not offered BNPL



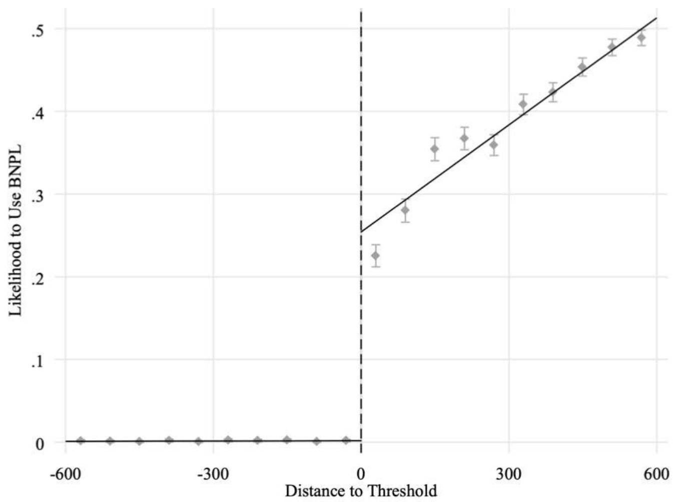
BNPL: Discontinuity at the Threshold

Descriptive evidence:

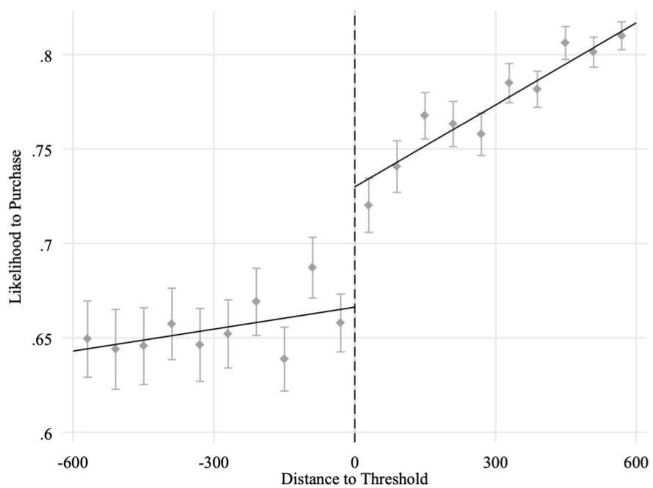
- BNPL offer likelihood jumps from 0% to 40%
- Likelihood using BNPL increases from 0% to 25%
- Conversion rate increases from 67% to 73%
- +40PP of customers with access to BNPL leads to +6PP higher conversion rate → 6/40 ~15% of customers only buy because BNPL is offered



(A) Probability to Offer Buy-Now-Pay-Later



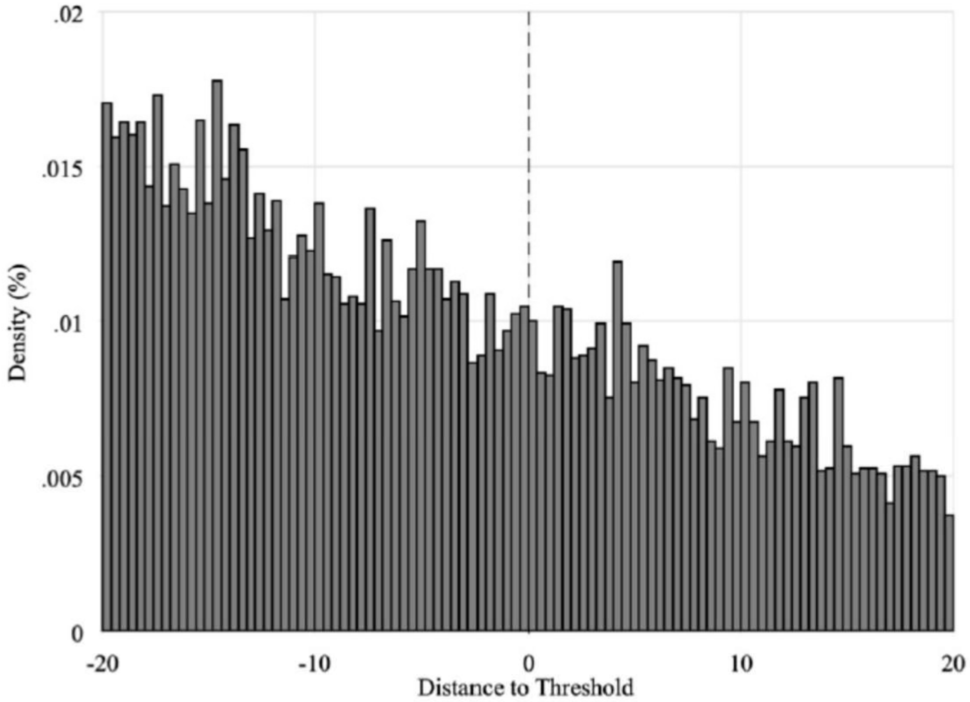
(B) Probability of Using Buy-Now-Pay-Later



(C) Probability of a Successful Conversion

BNPL: No manipulation of score

- Customers don't know exact method for calculating score



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2. Second stage
   - $Y_{i,t}$: Purchase (yes/no)
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BNPL: Results

- 16.5% of ALL customers abort the purchase if BNPL is not offered
- Recall: 50 / 100 customers choose BNPL
- So 16.5 / 50 that typically use BNPL abort (or 30%)

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
BNPL Offer (1/0)	0.152**	0.171**	0.165**
	(0.013)	(0.047)	(0.042)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	38	60	60
Observations	14,418	14,411	14,320

Conclusion

- We document the rise of payment firms
- Rise is closely linked to E-Commerce
- Clientele effect:
  - Customers' payment choices are sticky
  - Reluctance to switch to other payment type if favorite is not offered / favorite payment type not easy to use
- Can help to explains the existence of multiple payment firms that all have significant bargaining power over E-Commerce firms