Credit Card Market Power

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July 2026

The views expressed herein are those of the authors and not necessarily those of the Federal Reserve System.

Introduction

U.S. credit card industry:

1. Technology & reforms led to more competition & pass-through (Ausubel '91, Grodzicki '14)
2. Yet, wide spreads in Y-14 regulatory data (Dempsey, Ionescu '26), & very concentrated
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- Implement using origination dates on new Y14/OCC cards to build high-frequency rates
- Estimate model using differential pass-through, compute welfare losses

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- Main empirical contribution: move from documenting spreads to testing conduct

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- Welfare: Estimate model to match PT, then move to perfect competition
  - Rates fall 2.5pp, credit expands 145%, CE welfare gains $0.16\% - 0.45\%$

Data

- OCC/Y-14M Data: regulatory data, includes nine largest banks (75%+ of industry)
  - Credit card rates (r_{ij}), balances (l_{ij}), limits, and origination dates, 2008–2019
  - Origination dates let us build a daily event-time panel for 14 million new cards
  - Window: all originations from -3 to $+4$ weeks around each FOMC event

Market Definition

- We rely on three sources.

  1. Consulting reports by *McKinsey* (Fiorio et al '14)

     targeting by behavior and demographics, including income and geography.

  2. *Marketing and Acquisition* chapter of the *FDIC's 2007 Credit Card Activities Manual*

     markets by product line, geography, acquisition channel, and scoring.

  3. Academic marketing literature (Pellandini-Simanyi, 2023)

     customer groups shape card design, development, and distribution.

Market Definition

- Based on these sources, we consider *two* definitions of a market
  1. Baseline market: FICO $\times$ CC / product type $\times$ Loan Channel $\times$ Income Ventile
     - FICO is subprime ($\leq$ 600), near-prime (600-660), prime (660-780), super-prime ($>$ 780)
     - CC / product type is co-brand or not / general purpose or not
     - Loan channel is pre-approved/internet/other
     - Income ventiles based on 5-digit zip-code-level income

     $\Longrightarrow$ 960 possible markets
  2. Naive market: Drops loan-channel dimension and coarser FICO/income bins
     - FICO is subprime ($<$ 680) or prime ($\geq$ 680)
     - Income terciles based on zip-code-level income

     $\Longrightarrow$ 24 possible markets
- Our analysis focuses on *baseline* market definition; show robustness for the naive market

Summary Statistics: Borrower Traits (2008-2019)

Panel (a): Continuous Variables					Panel (b): Indicator Variables		
Variable	**Mean**	**Median**	**S.D.**	**Obs.**	**Variable**	**Fraction**	**Obs.**
APR	20.7%	22.0%	5.1%	15,340,327	General purpose	47.27%	15,340,327
Effective APR	16.9%	20.0%	7.9%	8,684,636	Co-brand	24.62%	15,340,327
Credit score	728	735	72	15,340,327	Internet channel	65.83%	15,340,327
Credit limit	4,980	3,300	5,446	15,321,038	Fixed interest rate	23.02%	15,288,106
Self-reported income	39,332	23,411	879,658	12,132,083	Promo balances	10.08%	14,840,257

- Large dataset, rich heterogeneity; some significant right-tails (e.g., income)
- 1/2 of accounts are GP; 1/4 co-brand; 2/3 internet channel

Empirical Facts

1. Market shares have fat right tail $\rightarrow$ average HHI of 0.47 (high concentration)
2. National shares also exhibit fat right tail Go
3. Banks have large national footprint, operate in $\approx$ 200 markets on average Go
4. Market-level shares explain 30% of rate variance Go
5. Near-identical borrowers pay dispersed rates, tracking dispersion in market shares Go

Facts 4 and 5 are correlational $\rightarrow$ theory delivers testable causal implications

Empirical Design: The Idea

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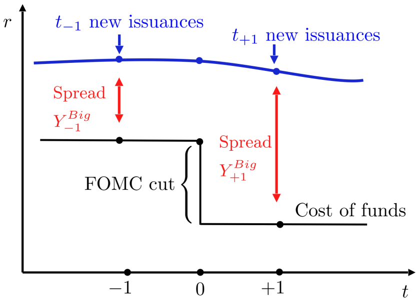
(a) Bank A - Dominant Player



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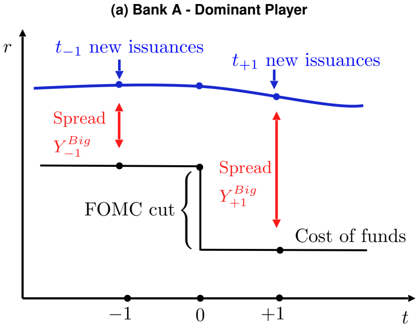

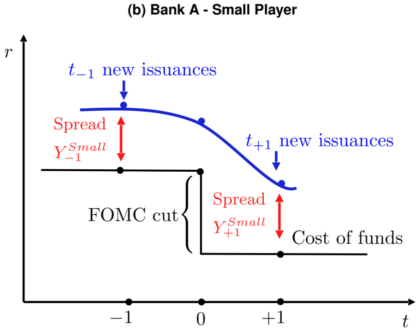

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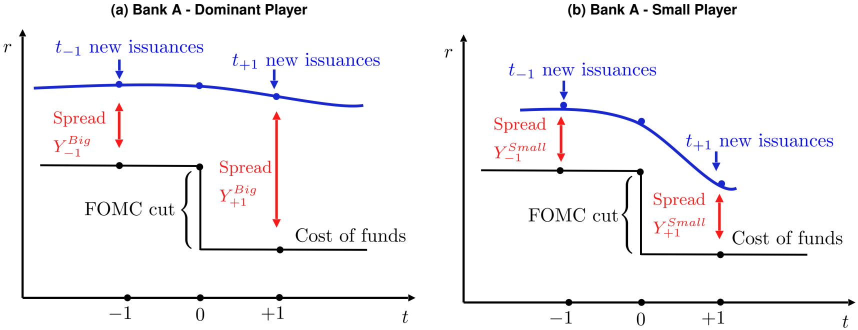

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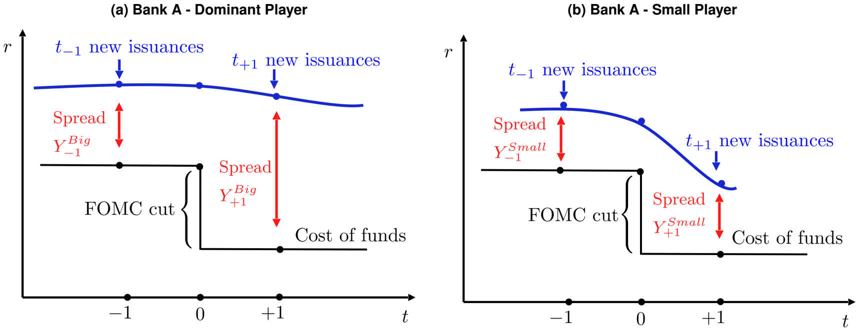

- $FF_t < 0 \rightarrow$ larger spread if large market share $\rightarrow$ expect negative loading in regression
- In practice, APR also reflects borrower risk – removed in the empirical implementation

Empirical Design: Roadmap

1. Remove time-varying borrower risk & funding costs from newly set APRs

   $\Rightarrow$ spread Y_{nt}: residualized log APR of account n at time t

2. Collapse into bank $\times$ market $\times$ event-week cohorts

3. Local projections: Does PT vary with lender's

   - market-level share (s_{ij}) [Test 1]
   - national importance (s_{ij}^{N}), fixing s_{ij} [Test 2]

- Identification is within-bank: same issuer, same event week, large vs. small positions

Step 1: Remove Time-Varying Risk and Costs

- Newly set APRs bundle three components:

$$\ln \text{APR}_{nt} = \underbrace{\text{bank costs}}_{\text{bank}\times t} + \underbrace{\text{default risk}}_{\text{card-level}} + \underbrace{\text{spreads}}_{s_{ij},\ s_{ij}^{N}}$$

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- Fixed-effects regression separates them:
  1. Bank costs: bank $\times$ time FEs ✗Remove
  2. Default risk: 'kitchen sink' of 11 card-level controls — bins on FICO, income, limit, ... ✗Remove
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- Spread: $Y_{nt} = \hat{\epsilon}_{nt} + \widehat{\text{share} \times \text{time FEs}}$ (market & national) ▸ Full spec. ▸ Distrib.

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- Compare cohorts of newly issued cards before vs. after the FOMC shock, across lender-market positions

Step 2: Local Projection Specification

- Horizon-h response of spreads, relative to pre-FOMC: $\Delta_h Y_{ij\tau} = Y_{ij,\tau+h} - Y_{ij,\tau-3}$
- LP specification:

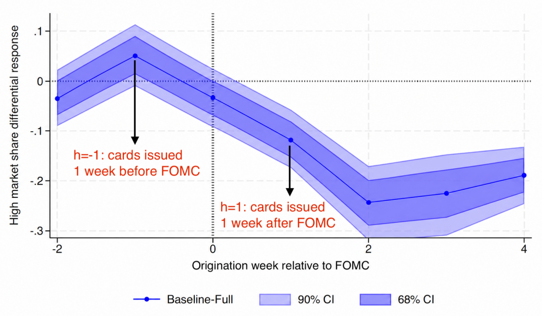
$$\Delta_h Y_{ij\tau} = \beta_{0h} + \beta_{Mh} FF_\tau \cdot \mathbb{I}^M_{ij\tau} + \beta_{Nh} FF_\tau \cdot \mathbb{I}^N_{ij\tau} + \rho_{1h} Y_{ij,\tau-3} + \alpha_{j\tau h} + e_{ij,\tau+h} \tag{1}$$

  - FF_τ: Fed Funds surprise
  - $\mathbb{I}^M_{ij\tau} = 1$ if bank i is large in market j $(s_{ij} > p70)$
  - $\mathbb{I}^N_{ij\tau} = 1$ if the ij position is nationally important $(s^N_{ij} > p98)$
  - $\alpha_{j\tau h}$: market $\times$ event FEs

- $\beta_{Mh} < 0$: lenders with high within-market shares have lower PT [Test 1]
- $\beta_{Nh} < 0$: nationally important positions have lower PT, fixing within-market share [Test 2]

January 2008 - Market-level: weekly window around rate cut at $t = 0$

(a) By market-resid combination, 70^{th} percentile s_{ij}



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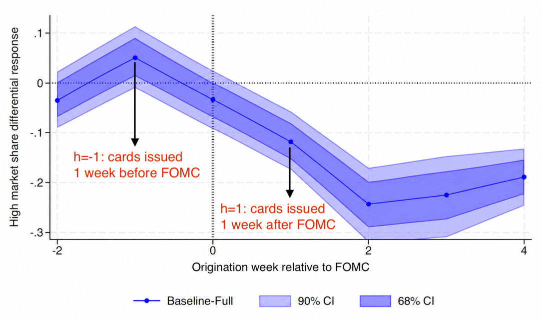

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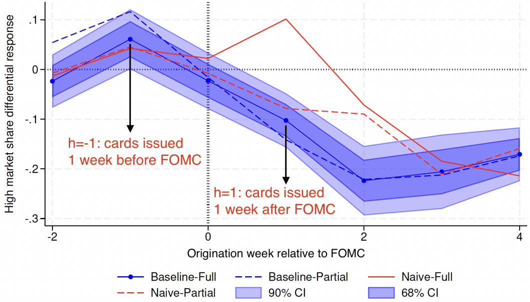

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  Dashed: partial residualization; red: naive market definition

Details semi-elast   Resid Alternatives

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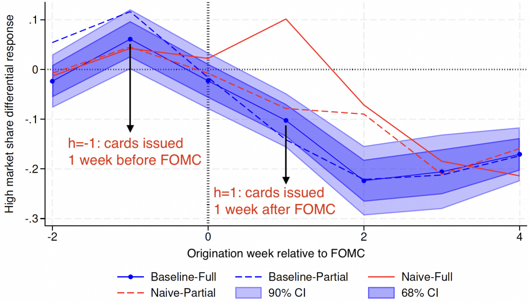
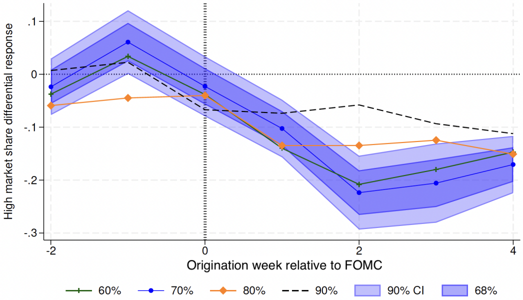


(b) By s_{ij} cutoff, baseline-full specification



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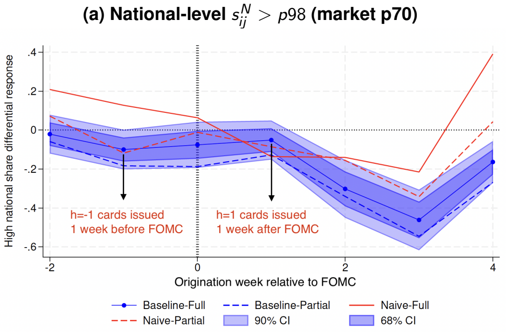

- Pass-through 20% lower in high s_{ij}^N markets vs. low s_{ij}^N markets of same bank

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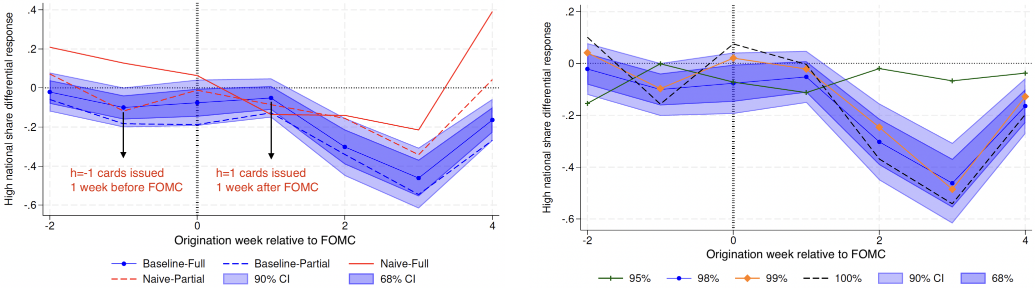
January 2008 - National-level: weekly window around rate cut at $t = 0$

(a) National-level $s_{ij}^N > p98$ (market p70) **(b) By s_{ij}^N cutoff, controlling for 70^{th} s_{ij}, baseline-full**



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Dashed: partial residualization; red: naive market definition

Alternative Adjustment Margins: 70^{th} perc. s_{ij} cutoff, January 2008

Table: Market-level: average response over horizons 1-4, baseline market

	Balances (1)	Fees (2)	Limits (3)
Full residualization	-24.94	1.83	-39.57
	(96.10)	(1.29)	(297.65)
Partial residualization	47.93	6.10	-238.78
	(107.34)	(1.73)	(287.28)
Lagged dependent	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes

- Estimates for alternative adjustment margins are very small or statistically insignificant

Robustness - Market-level: By sample & market def, 70^{th} percentile s_{ij}

OLS: $$\frac{1}{4}\sum_{h=1}^{4}\Delta_h Y_{ij,\tau} = \bar{\beta}_0 + \bar{\beta}_M\, FF_\tau \cdot \mathbb{I}_{ij,\tau}^{M,high} + \bar{\beta}_N\, FF_\tau \cdot \mathbb{I}_{ij,\tau}^{N,high} + \bar{\rho}_1 Y_{ij,\tau-3} + \bar{\alpha}_{j\tau} + \bar{\varepsilon}_{ij,\tau}$$

Table: Market-level: average response over horizons 1-4, baseline market

	January 2008 (1)	Big cuts 2008 (2)	All 2008 (3)	All events (4)
Full residualization	-0.18	-0.22	-0.09	-0.06
	(0.03)	(0.02)	(0.02)	(0.02)
Partial residualization	-0.19	-0.30	-0.13	-0.11
	(0.03)	(0.02)	(0.02)	(0.02)
Lagged dependent	Yes	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes	Yes

- Stacking events (positive and negative shocks) mitigates results but still significant Natl.

Additional Empirical Results

1. Results hold for APR in levels Go and log effective APR Go
   - Effective APR = (1 - share promos) x APR
2. Results hold for alternative measures of MP shocks (2008-2019) Go
   - MP shocks: FF4, principal component (Fed funds 1-6, Eurodollars 1-6), news-adjusted
3. Results hold independently for subprime and prime accounts Go; and geography Go

Model Estimation: Overview

- Feed in the observed industry structure:
  - $N = 9$ national lenders, $J = 960$ markets, as in OCC
  - Match distribution of banks across markets, costs, and market sizes
- Estimate market power to match the empirical evidence: Mechanism
  - Within-market competition $\rightarrow$ average HHI
  - Cross-market power & demand curvature $\rightarrow$ model must reproduce the 17% and 20% lower PT from the event studies [Tests 1 & 2]
  - Scale of credit $\rightarrow$ revolving credit-to-GDP
- Model fit: untargeted share distributions match data Details Calib Fit Spreads Revolvers

Welfare costs of market-level v. national-level oligopoly

- Experiment: re-solve for equilibrium, removing each layer of market power in turn
- Rates fall by 2.5pp, credit expands by 145%, CE welfare gain $.16\% - .45\%$ Reallocation

	(1) National Oligopoly	(2) Market Oligopoly	(3) Monopolistic Competition	(4) Perfect Competition
Average interest rate (Percent)	7.03	7.01	6.57	4.50
Credit to GDP (Percent)	16.76	17.17	24.84	41.08
National HHI	0.46	0.46	0.55	0.55
Profit to GDP (Percent)	0.29	0.28	0.22	0.00
Welfare gain leaving national eq. (%)	–	0.006	0.099	0.161
Welfare gain leaving national eq., Π fixed (%)	–	0.009	0.165	0.448

Conclusion

- New theory of national issuers $\rightarrow$ testable predictions on conduct
- Origination dates in Y-14/OCC $\rightarrow$ high-frequency rates on new cards
- Pass-through around FOMC events rejects competitive benchmarks:
  - 17% lower PT in a bank's high market-share markets [Test 1]
  - 20% lower PT in nationally important positions [Test 2]
- Estimated model: moving to perfect competition, rates fall 2.5pp, credit expands $\sim$145%, welfare gains 0.16–0.45%
- Takeaway: credit card market power operates at two levels: within markets and across the national industry

APPENDIX

Summary Statistics: Bank Traits (2008-2019)

- Let i denote bank, j denote market
- Market-level share: s_{ij} captures local impact

$$s_{ij} = \frac{r_{ij} l_{ij}}{\sum_i r_{ij} l_{ij}} \tag{2}$$

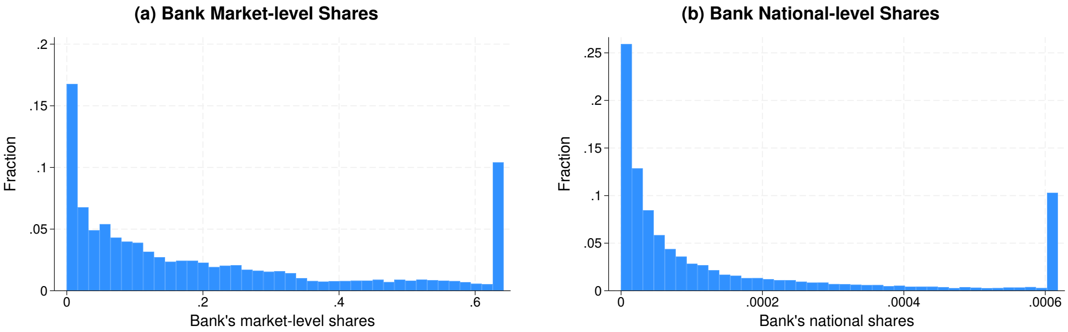
- (Model implied) National-level share: s_{ij}^N captures national impact

$$s_{ij}^N = \frac{r_{ij} l_{ij}}{\sum_j \sum_i r_{ij} l_{ij}} \tag{3}$$

$\rightarrow$ importance of a bank in a given market ($r_{ij} l_{ij}$) relative to national industry ($\sum_j \sum_i r_{ij} l_{ij}$)

- Despite a common numerator, s_{ij} and s_{ij}^N are *imperfectly correlated*

Distribution of Bank Market-level Shares (Winsorized at top 10%)



- Right-tailed market-level shares dist.; HHI index is 0.47 indicating high concentration
- National-level shares distribution also has a fat tail

Tabulations Back

Motivating Market Power: FE Variance Decomposition

- Leverage on *account-level* data on credit card originations (2008-2019)
- Estimate high-dimensional FEs regression; provide standard variance decomposition

Table: Variance Decomposition, X-by-time FEs

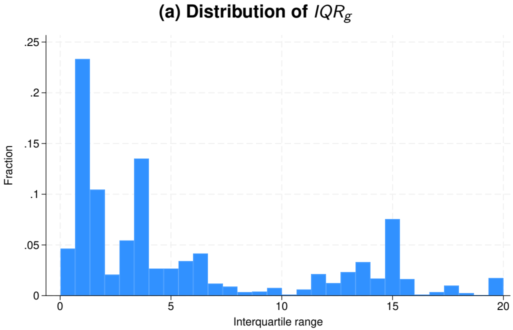
	Market Share	**National Share**	**Bank FE**	**Market FE**	**Borrower FE**
Market Share	0.304				
National Share	-0.047	0.210			
Bank FE	-0.017	-0.019	0.153		
Market FE	-0.129	-0.157	0.101	0.572	
Borrower FE	-0.010	0.013	-0.034	0.014	0.089

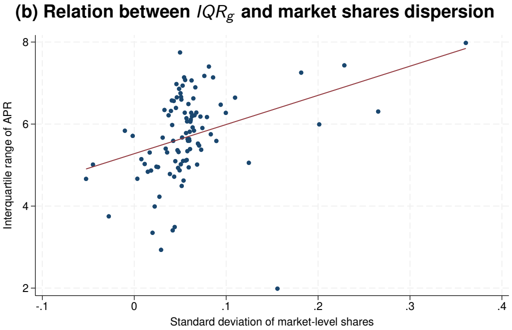
- Combined covariates explain 75% of variation in interest rates

Overall: Market-share variation account for significant rate variation

Evidence not causal $\Longrightarrow$ develop theory with empirically testable implications Back

Motivating Market Power: Matched Cards



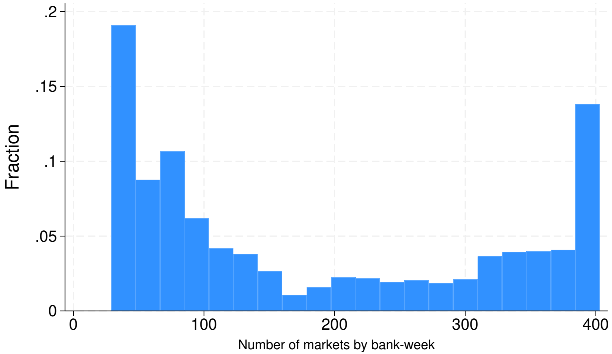


- Average rate IQR is 5.7 pp → significant dispersion even among finely-matched cards
- High correlation with market-level share dispersion (R2 of 60%)

Overall: Market-share variation account for significant rate variation

Evidence not causal $\implies$ develop theory with empirically testable implications Back

Distribution of Number of Markets (Winsorized at low/top 10%)



- Median bank issues credit cards in $\approx$ 130 markets in any given week
- Fat tail, with inter-decile range of $\approx$ 370 markets

Back

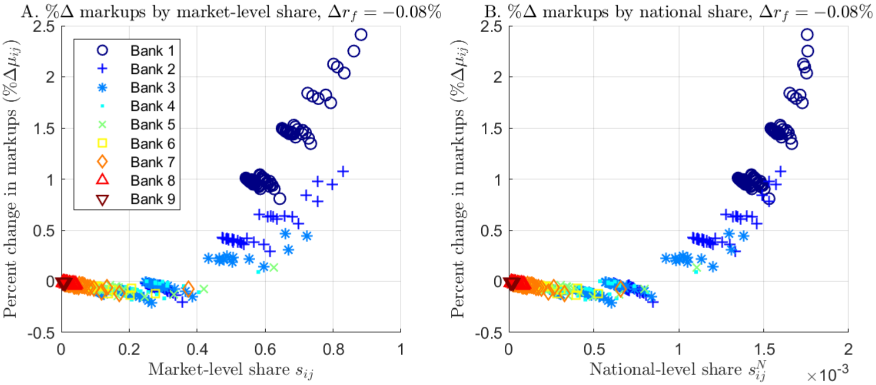
Frequency by Market Definition (2008-2019)

Panel A: Baseline market			Panel B: Naive market		
	National low	National high		National low	National high
Market low	322,083	5,346	Market low	23,976	161
Market high	204,047	22,495	Market high	12,739	1,250

Back

General Characterization: Adjustment of Markups Upon Rate Cut

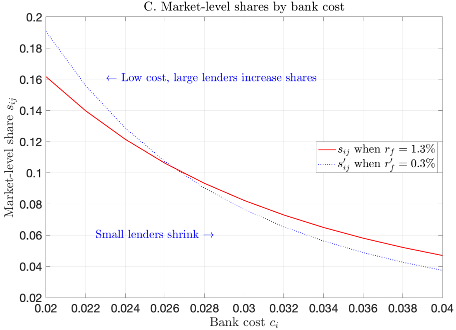
- Simulate a 8 bps reduction in r_f

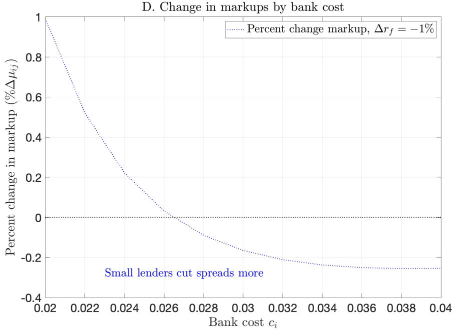


- Differential pass-through across distribution of shares Stylized version Back

Market-level Oligopoly: Pass-through From Risk Free Rate to Markups

Assume rate cut by 1%, with c_i evenly spaced over $[\underline{c}, \overline{c}] = [.02, .04]$





- Larger banks expand their market shares, increase markups (opposite for smaller banks)
- Our empirical strategy is designed to recover markup dynamics Back

Two Residualization Alternatives

Our analysis includes two alternative residualization strategies.

1. Partial residualization: parsimonious set of borrower FEs
   - Bins on FICO and self-reported income (deflated by CPI)
   - Flags on multiple banking relations, multiple credit cards, secured, and securitized status

2. Full residualization: more flexible set of FEs
   - Bins on credit limits, cycle ending balance, and utilization rate
   - Flags on interest rate type and promotional balances

Back

Details on Residualization

- Let n be individual, $i(n)$ bank, $j(n)$ market, t date
- For each event, residualize log APR based on

$$\log APR_{nt} = \beta_0 + w_t + dow_t + \alpha_j + \widetilde{sh}^M_{ijt} + \widetilde{sh}^N_{ijt} + \alpha_i + FS_n + \Gamma X_n + ... \\ + w_t \cdot \left(\widetilde{sh}^M_{ijt} + \widetilde{sh}^N_{ijt}\right) + w_t \cdot (\alpha_i + FS_n + \Omega_t X_n) + \epsilon_{nt} \quad (4)$$

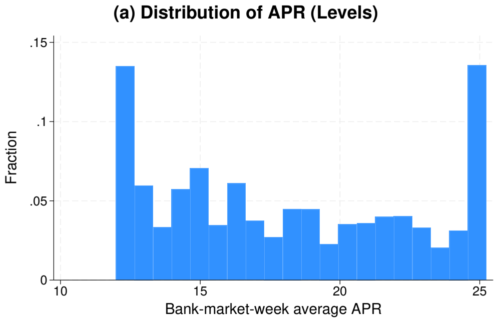
  - w_t week FE, dow_t day-of-week FEs, α_j market FEs, α_i bank FEs, and $\widetilde{sh}^M_{ijt}$ and $\widetilde{sh}^N_{ijt}$ FE for quantiles of banks' market- ($\tilde{s}_{ijt}$) and national-level shares ($\tilde{s}^N_{ijt}$)
  - FS_n denote 40 bins of an individual's FICO score
  - X_n vector of additional borrower-level controls

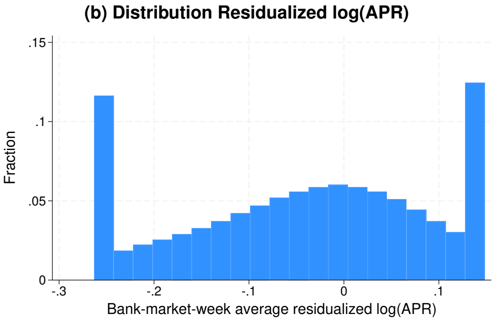
- Residualized spreads are computed as

$$Y_{nt} = \hat{\epsilon}_{nt} + \widehat{w_t \cdot \widetilde{sh}^M_{ijt}} + \widehat{w_t \cdot \widetilde{sh}^N_{ijt}} \quad (5)$$

where *hatted* variables denote projected values back

Distribution of APR (Winsorized low/top 10%)





Residualized (log) APR exhibits significant dispersion to be exploited in regressions back

Main results: Interpretation of β_{Mh}

- β_{Mh} within $[-0.25, -0.10]$ at horizons 1-4
- What does $\beta_{Mh} = -0.17$ mean for differential pass-through?
- β_{Mh} is a semi-elasticity (log interest rates on LHS, non-log FF on RHS)

$$\frac{d\ln(APR)}{dFF} = \frac{1}{APR}\frac{dAPR}{dFF} = \beta_{Mh}\mathbb{I}_{jm}^{high}$$

$$\Rightarrow \quad \frac{dAPR^{high}}{dFF} - \frac{dAPR^{low}}{dFF} = \beta_{Mh} \times APR$$

- If $\beta_{Mh} = -0.17$ & avg. residual APR is 1.02pp, high market-level share has 17% lower PT

Back

Robustness - National-level: 98^{th} perc. s_{ij}^{N}, controlling for 70^{th} perc. s_{ij}

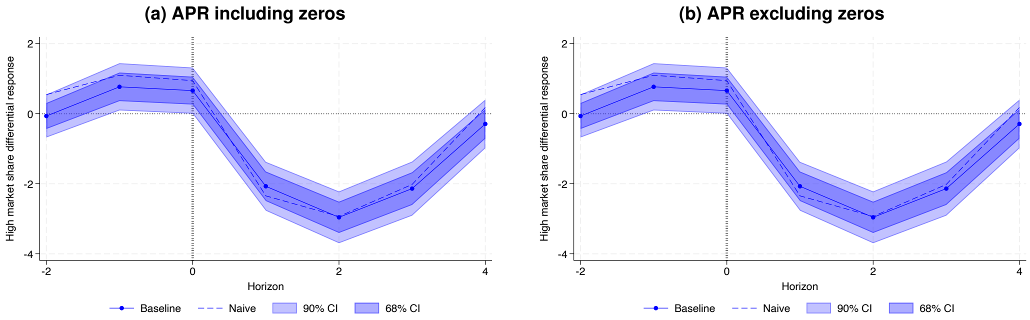
OLS: $$\frac{1}{4}\sum_{h=1}^{4}\Delta_h Y_{ij,\tau} = \bar{\beta}_0 + \bar{\beta}_M\, FF_\tau \cdot \mathbb{I}_{ij,\tau}^{M,high} + \bar{\beta}_N\, FF_\tau \cdot \mathbb{I}_{ij,\tau}^{N,high} + \bar{\rho}_1 Y_{ij,\tau-3} + \bar{\alpha}_{j\tau} + \bar{\varepsilon}_{ij,\tau}$$

	January 2008 (1)	Big cuts 2008 (2)	All 2008 (3)	All events (4)
Baseline market				
Full residualization	-0.24	-0.14	0.01	-0.04
	(0.05)	(0.05)	(0.05)	(0.04)
Partial residualization	-0.32	-0.27	-0.02	-0.07
	(0.06)	(0.05)	(0.06)	(0.04)
Naive market				
Full residualization	-0.03	-0.08	0.09	0.08
	(0.16)	(0.13)	(0.11)	(0.10)
Partial residualization	-0.14	-0.13	0.03	0.04
	(0.10)	(0.10)	(0.10)	(0.09)
Lagged dependent	Yes	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes	Yes

- For Jan 2008 and big cuts 2008, estimate for $\bar{\beta}_N$ negative & significant
- Estimate ≈ 0 when stacking, need large cuts for identification Back

Differential Pass-through for APR, Market-level 70^{th} perc. s_{ij}, January 2008

- Switch left-hand side of LP to residualized APR (levels)



- Qualitative results hold for APR (with and w/o zeros) Back

Robustness: Alternative Rate Definitions, January 2008

- Differential PT at market-level 70^{th} perc. s_{ij}, alternative outcome definitions

	APR (level) (1)	APR (positive) (2)	$\log($Eff. APR$)$ (3)
Full residualization	-2.01	-1.97	-0.17
	(0.36)	(0.29)	(0.04)
Partial residualization	-1.95	-2.22	-0.22
	(0.47)	(0.32)	(0.04)
Lagged dependent	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes

- Results hold in levels (with and w/o zeros) and for log effective APR Back
  - Effective APR $=$ (1 $-$ share promos) $\times$ APR

Robustness: Alternative monetary policy shocks

- Stacked events 2008-2019; principal component and news-adjusted shocks Back

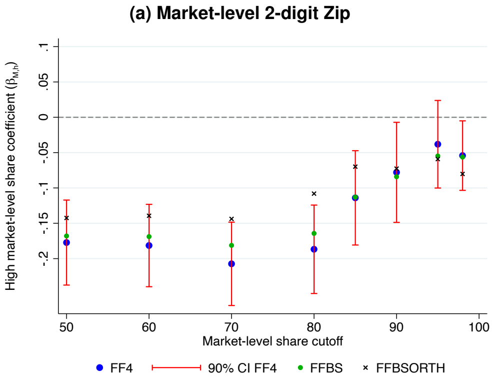
	FF4 (wide) (1)	FF4 (tight) (2)	Princ. Comp. (3)	News-adjusted (4)
Full residualization	-0.06	-0.07	-0.13	-0.09
	(0.02)	(0.03)	(0.02)	(0.02)
Partial residualization	-0.11	-0.16	-0.22	-0.15
	(0.02)	(0.03)	(0.02)	(0.02)
Lagged dependent	Yes	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes	Yes

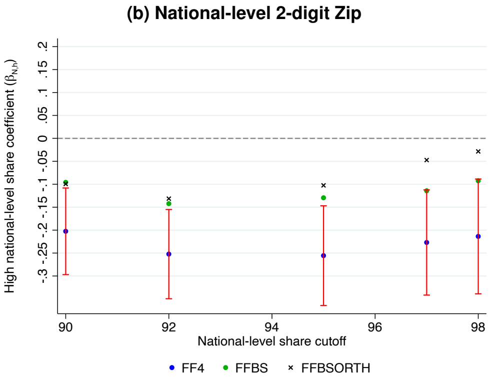
Robustness: Regressions by FICO (market 70^{th} perc. s_{ij})

- Run local projections separately for subprime and prime accounts Back

	January 2008		All events	
	Subprime (1)	Prime (2)	Subprime (3)	Prime (4)
Full residualization	-0.13	-0.18	-0.09	-0.08
	(0.07)	(0.03)	(0.04)	(0.02)
Partial residualization	-0.14	-0.24	-0.13	-0.14
	(0.07)	(0.04)	(0.04)	(0.02)
Lagged dependent	Yes	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes	Yes

Results 2-digit Zip - Differential pass-through by market- and national-level shares





- Point estimates similar to baseline analysis Back

Model Estimation

Preferences: GHH, set shifter A to hit revolving credit-to-GDP $u(C_1, L) = C_1 + A\frac{L^{1-\gamma}}{1-\gamma}$

Model Estimation

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Parametric distributions: $N = 9$ national lenders, $J = 960$ markets

1. Fit banks per market N_j with Gamma distribution over $\{1, ..., N\}$ Dist.
2. Uniform bank costs $c_i \sim U[\underline{c}, \overline{c}]$ to match r_{ij} mean, variance
3. Probability bank i operates in market j inversely proportional to cost $P_{ij} \propto -b \times c_i$
4. Tastes log-linear in market size $\phi_j = \frac{exp(\beta N_j)}{\sum_j exp(\beta N_j)}$ to hit fat s_j tail

Model Estimation

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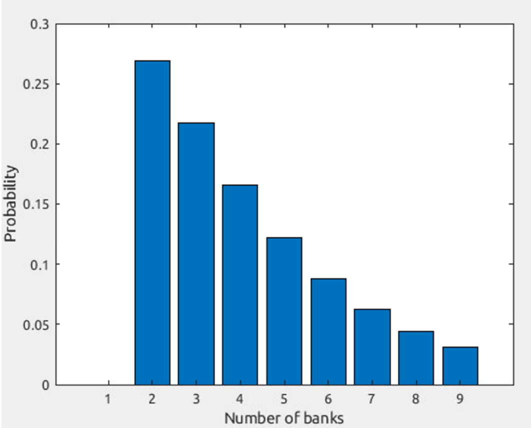
Market power: w/in-market η, x-market θ, curvature on credit services γ

1. η identified from average HHI
2. γ and θ identified from differential market- and national- pass-through rates Calib table Back

Target: Distribution of Number of Banks per Market

- Fitted gamma distribution with scale=4.4 and shape=1.5 Back



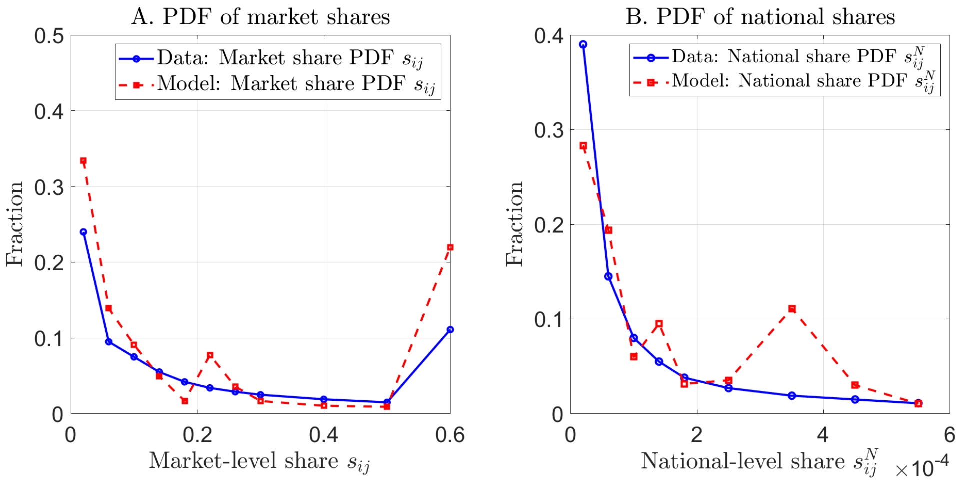
Model Estimation: Results

Var.	Description	Value	Moment	Model	Data
A	Credit Service Utility Shifter	0.11	Credit to income	0.168	0.168
$\underline{c}$	Lower bound bank cost of funds	0.001	Average of r_{ij}	0.070	0.061
$\overline{c}$	Upper bound bank cost of funds	0.08	Standard deviation r_{ij}	0.032	0.045
η	Intramarket elasticity	3.17	Average HHI	0.493	0.470
θ	Intermarket elasticity	1.46	Slope s_{ij} p70	-0.171	-0.173
γ	Curvature over credit services L	0.75	Slope s_{ij}^N p98, controlling s_{ij} p70	-0.120	-0.114
b	Cov. ownership prob. & bank cost	4.31	SD of number of markets each bank operates in	137.25	149.00
β	Cov. taste & market size	9.9e-03	s_{ij}^N 90^{th} percentile	0.0006	0.0006

- Elasticities imply spreads of 0.5pp (3.2pp) in most (least) competitive markets

Back

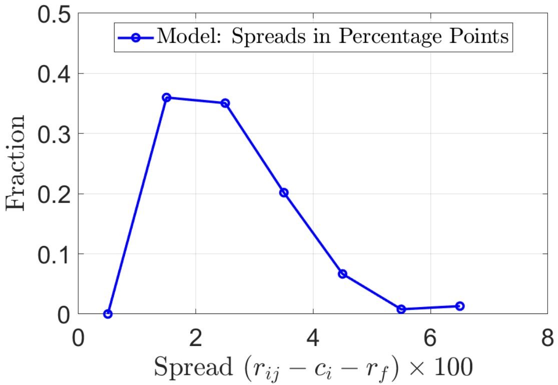
Model Validation: Market and national-level shares in model versus data



- Model matches data relatively well, with some miss-prediction in tails

Back

Model Implied Credit Card Interest Rate Spreads

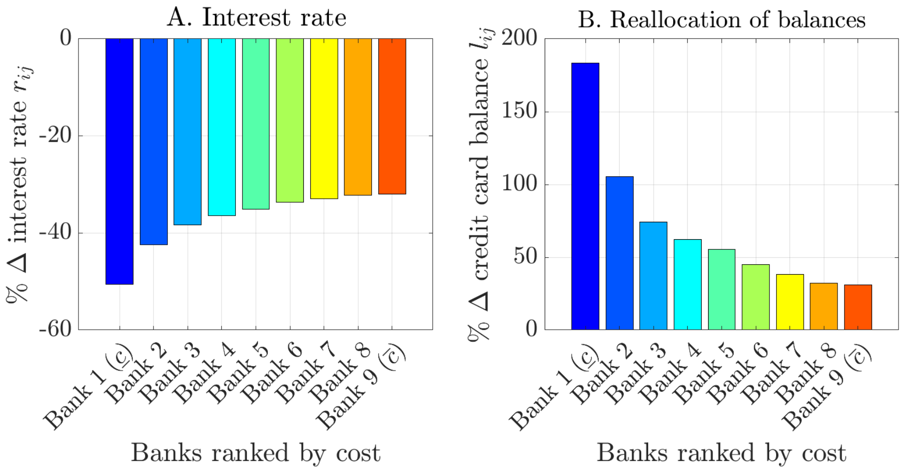


Back

Reallocation drives welfare gains

Figure: Interest rates & balance reallocation, national to competitive

Back



Fraction revolvers

- SCF: *"After the last payment was made on this account, what was the balance still owed on this account?"*
- 67% of new applicants had positive balance in '07 or in '09 panel, 12% in 10^{th} income decile, 29% in 9^{th} income decile

Variable	Mean	SD	N
Hardly/Sometime repay 2007	0.39	0.49	2757
Hardly/Sometime repay 2009	0.38	0.48	2757
Ever positive balance, new applicants (any loan) 2007-2009	0.67	0.47	2133
Hardly/Sometime repay, new applicant (any loan) 2007-2009	0.56	0.50	2133

- Y14s: 30-40% of prime individuals revolve within first 12m of origination

	2014		2008	
	Prime	Subprime	Prime	Subprime
Mean	31.6%	57.0%	42.5%	64.4%
Median	31.4%	56.3%	43.0%	64.3%

back

Monetary Policy Back

- The shocks used as benchmarks for the selection of events are labeled FF4, FFJK, and FFBS, and are constructed, respectively, as:
- the change in the 3-month ahead Fed Funds rate futures over a 30-minute window around the FOMC announcement;
- the first principle component over surprises in the current month and 3-month ahead Fed Funds futures and in the first four quarterly Eurodollar futures contracts, ED1ED4;
- and the first principal component of surprises in ED1ED4. These measures were constructed by Jarocinski Karadi (2020) and Bauer Swanson (2023), and are publicly available online.
- An FOMC event is included in our analysis if either of these shocks is greater or equal than 5 bps in absolute value.

Table: FOMC Events

22jan2008 (-)	25jun2008 (-)	23sep2009 (-)	28oct2015 (+)
30jan2008 (-)	16sep2008 (+)	21sep2011 (+)	16mar2016 (-)
11mar2008 (+)	16dec2008 (-)	17dec2014 (-)	20sep2017 (+)
18mar2008 (+)	18mar2009 (-)	18mar2015 (-)	19jun2019 (-)
30apr2008 (-)	24jun2009 (+)	17sep2015 (-)	31jul2019 (+)