

Do Banks Pass Through Credit Expansions to Consumers Who Want to Borrow?

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Motivation

- In response to Great Recession, key policy objective was to provide banks with lower-cost capital and liquidity
- One motivation was to stimulate aggregate demand » Policy Motivatoin
 - ↓ Cost of funds \Rightarrow ↑ Credit availability \Rightarrow ↑ Borrowing, spending, investment
- Challenging to analyze effectiveness of this “bank lending channel” using time-series analysis.
 - Changes in banks' cost of funds are usually correlated with other forces that affect credit demand and supply.

This Paper

- 1 Propose new approach to studying bank lending channel
 - Can be implemented using micro-data on lending + quasi-exogenous cross-sectional variation in contract terms
- 2 Use approach to study U.S. credit card lending during Great Recession
 - Marginal source of credit for most households
 - Analyze forces that affected effectiveness of bank-mediated stimulus during this time period

Our Approach

- Credit card market primarily adjusts through credit limits
- Aggregate impact of decrease in cost of funds (c) on borrowing (q):

$$-\frac{dq}{dc} = \int_i \underbrace{-\frac{dCL_i}{dc}}_{\text{MPL}} \times \underbrace{\frac{dq_i}{dCL_i}}_{\text{MPB}}$$

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- **Empirically Useful:** Decomposes total effect into objects we can estimate quasi-exogenous variation.
- **Conceptually Useful:** At the margin, is total borrowing is constrained by credit supply (low MPL) or credit demand (low MPB)?
 - How does this differ across the population?

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 - How does this differ across the population?
- **Estimate heterogeneous MPB & MPL in U.S. credit card market**

Our Approach

- Data: Universe of credit card accounts issued by 8 largest U.S. banks
- Research design: Some banks set credit limits as step-function of FICO
 - ⇒ 743 RDs in all parts of the FICO score distribution
- Directly estimate heterogeneous MPBs
 - MBP strongly decreasing in the FICO score
- Simple model to express optimal MPL in terms of "sufficient statistics"
 - Can be estimated using credit limit RDs.
 - MPL strongly increasing in FICO score
- Household Borrowing in Great Recession: Credit supply vs. demand
 - Supply important for low FICOs, demand for high FICOs
 - Banks don't want to lend (more) to those that want to borrow (more).

Outline

- **Data**
- Research Design
- Marginal Propensity to Borrow
- Marginal Propensity to Lend

Data

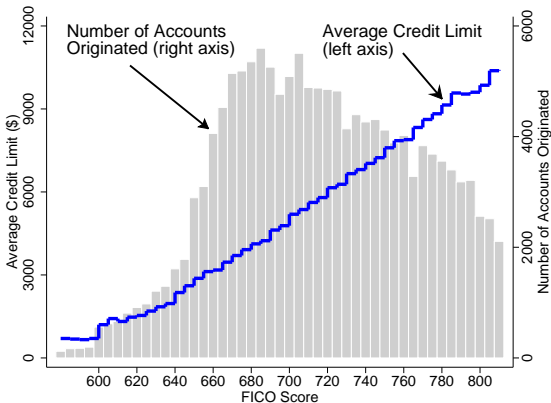
- OCC Credit Card Metrics
 - All credit cards issued by 8 largest U.S. banks
 - 400 million credit card accounts
 - Monthly data from January 2008 to December 2014
- Key variables
 - Spending and borrowing information \Rightarrow MPB
 - Interest payments, fees and chargeoffs \Rightarrow MPL
 - Merged in credit bureau information
- Sample restrictions
 - Focus on cards originated within our sample (since January 2008)

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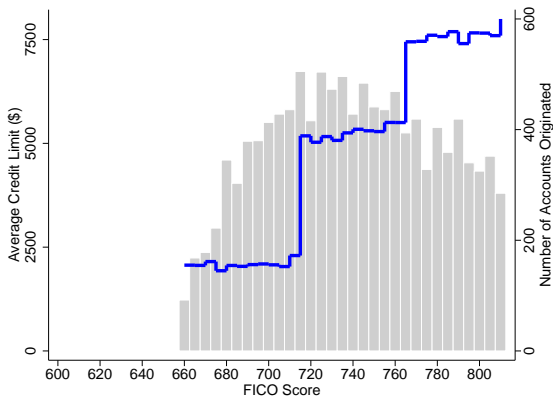
Credit Limit Quasi-Experiments

- Credit card lenders assign credit limit based on FICO credit score
- Might also consider other factors (e.g., internal behavioral scores)



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RD Estimator

- Fuzzy RD estimator for a given experiment

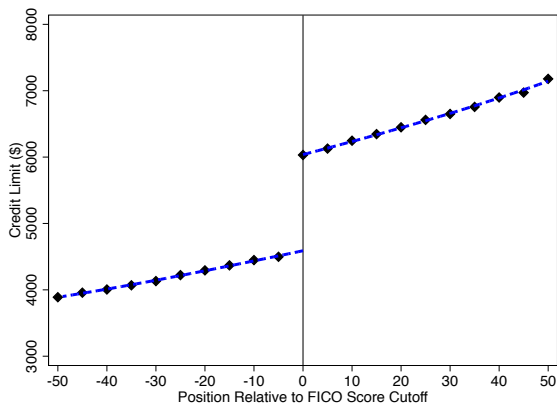
$$\tau_j = \frac{\lim_{FICO \downarrow \overline{FICO}} E[Y|FICO] - \lim_{FICO \uparrow \overline{FICO}} E[Y|FICO]}{\lim_{FICO \downarrow \overline{FICO}} E[CL|FICO] - \lim_{FICO \uparrow \overline{FICO}} E[CL|FICO]}$$
$$= \frac{\text{"Jump in outcome"}}{\text{"Jump in CL"}}$$

- Causal interpretation requires two assumptions:

A1: Other contract & borrower characteristics trend smoothly through cutoff

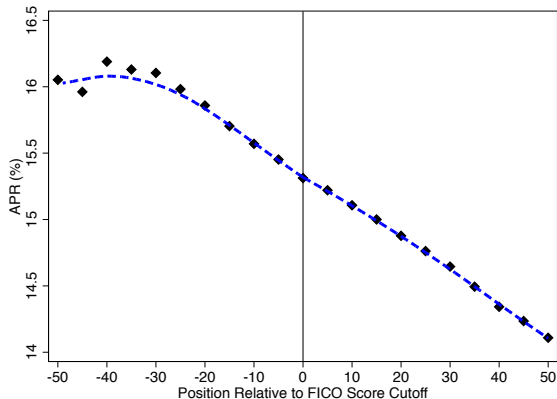
A2: No strategic movement around cutoff

First Stage on Credit Limits



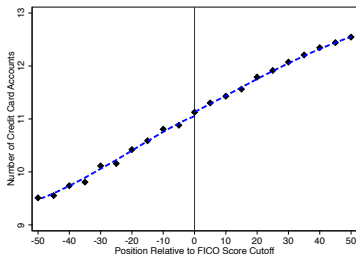
- Pooled across all quasi-experiments, centered around cutoff
- \$1,472 higher average credit limit around our cutoffs

A1: Interest Rate (APR) Trends Smoothly

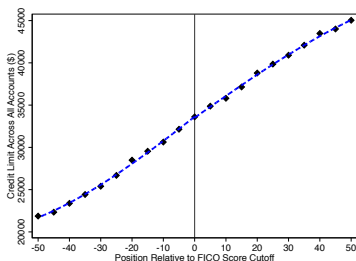


- No discontinuous change in interest rates around credit limit cutoffs.

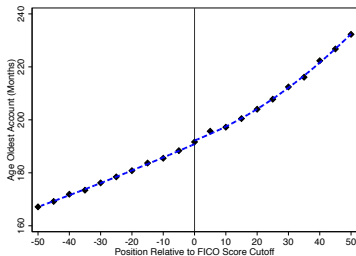
A1: Borrower Characteristics Trend Smoothly



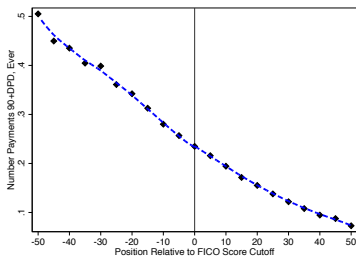
(a) Number of Credit Card Accounts



(b) Total Credit Limit (\$)

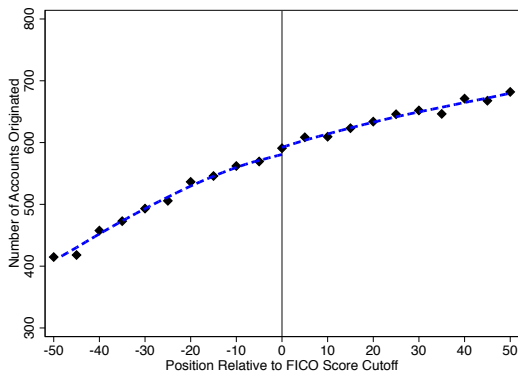


(c) Age of Oldest Account (Years)



(d) # of Payments 90+ DPD (Ever)

A2: No Strategic Movement Around Cutoff



- Hard to precisely manipulate FICO score
- Credit supply function not known
- Credit limit unknown when consumer applies for card (no demand response).

Aggregating Across Experiments

- Estimate τ_j separately for each quasi-experiment j [▶ Estimates](#)
 - Separate second-order local polynomial with Imbens-Kalyanaraman (2011) optimal bandwidth [▶ Details](#)
- Recover average effect by FICO group with regression

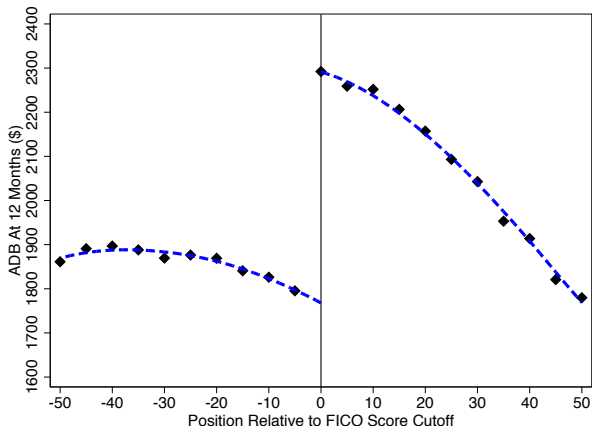
$$\tau_j = \sum_{k \in K} \beta_k FICO_k + X_j' \delta_X + \epsilon_j$$

- $FICO_k$ are FICO group quartiles
 - X_j are fully interacted bank \times origination quarter fixed effects
- Standard errors constructing by bootstrapping over experiments

Outline

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- **Marginal Propensity to Borrow**
- Marginal Propensity to Lend

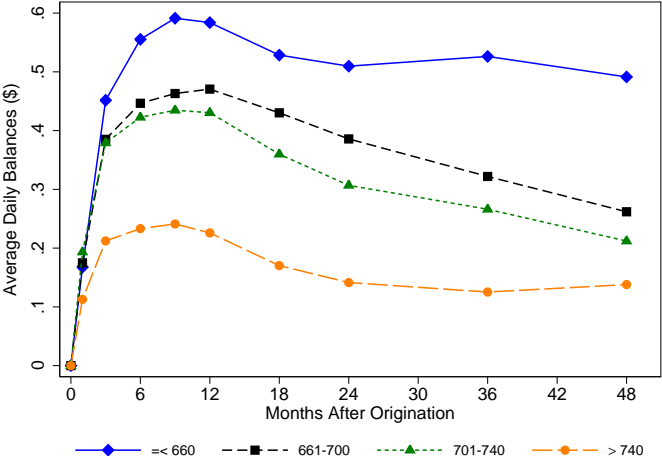
MPB on “Treated” Card, After 12 months



- Pooled across all quasi-experiments, centered on cutoff.

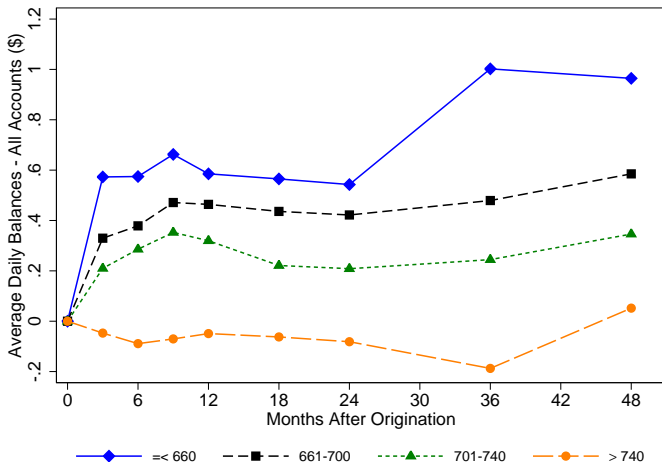
• [▶ Summary stats](#)

MPB on Treated Card, Heterogeneity



- Quick response, gradual decline
- Large heterogeneity by FICO score, even high FICO borrowers respond

MPB Across All Cards, Heterogeneity



- Lower-FICO borrowers: 1-for-1 increase in total borrowing
- FICO > 740 : No response in total borrowing \Rightarrow balance shifting

MPB Takeaway

- Substantial heterogeneity in borrowing / spending behavior
- $FICO \leq 660$
 - MPB of at least 50% on treated card
 - Not offset by decline on other cards
 - Corresponds to increase in spending on treated card [▶ Figure](#)

- $FICO > 740$
 - MPB of $\approx 15\%$ on treated card
 - Completely due to balance shifting
 - Zero MPB despite significant borrowing on average

⇒ Stimulating borrowing requires credit expansion to low-FICO households

Outline

- Data and Research design
- Marginal Propensity to Borrow
- **Marginal Propensity to Lend**
 - **Model**
 - Estimates

Marginal Propensity to Lend – MPL

- MPL: Effect on CL of a 1 ppt permanent reduction in cost of funds
- Cannot estimate using event-study approach.
 - Changes to Fed Funds rate typically correlated with macro shocks that shift bank expectations [▶▶ Figure](#)
- **Our approach:** Simple model of optimal CL that characterizes MPL with two sufficient statistics we can estimate directly.
 - Build on literature that shows CL, not interest rates, is primary margin of adjustment for credit card
- Tradeoff: To overcome identification challenge we require that:
 - Bank lending responds optimally to changes in cost of funds
 - We can measure banks' incentives to lend

Marginal Propensity to Lend – MPL

- Simple model of optimal CL for observably identical borrowers:
 - $q(CL)$ is quantity of borrowing
 - $F(CL)$ is fee revenue
 - $C(CL)$ is net chargeoffs
 - r is exogenously determined interest rate
 - c is cost of funds
- Bank objective function:

$$\max_{CL} q(CL)(r - c) + F(CL) - C(CL)$$

- First order condition:

$$\underbrace{q'(CL)r + F'(CL)}_{=MR(CL)} = \underbrace{q'(CL)c + C'(CL)}_{=MC(CL)} \iff MP(CL) = 0$$

Marginal Propensity to Lend – MPL

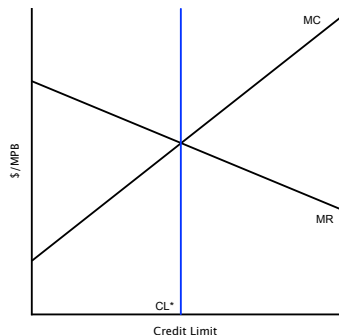
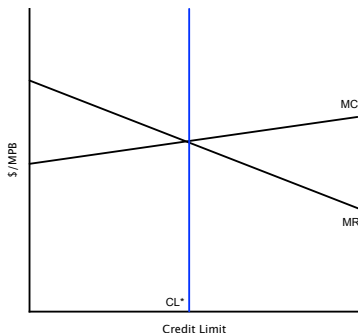
- Define MPL as $-\frac{dCL}{dc}$
- Applying implicit function theorem to FOC yields

$$MPL = -\frac{MPB}{MR'(CL) - MC'(CL)} = -\frac{MPB}{MP'(CL)}$$

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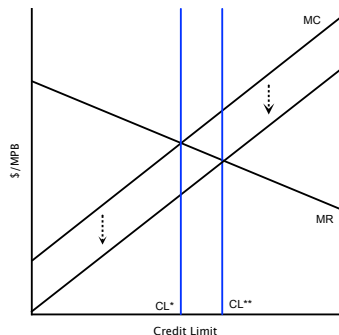
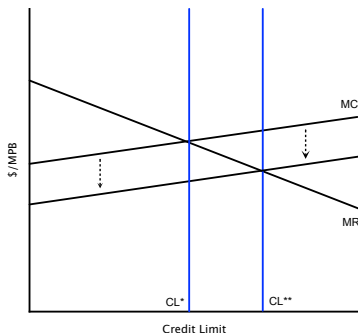
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Marginal Propensity to Lend – MPL

- Define MPL as $-\frac{dCL}{dc}$
- Applying implicit function theorem to FOC yields:

$$MPL = -\frac{MPB}{MR'(CL) - MC'(CL)} = -\frac{MPB}{MP'(CL)}$$



Economics Behind $MC'(CL)$

1. Adverse selection (changing marginal borrower)

- Larger increases in borrowing by households with higher default probability

2. Direct effect of higher credit limits (keeping marginal borrower fixed)

- Strategic models: Increased debt brings households closer to bankruptcy threshold (Fay, Hurst and White, 2002)
- Myopia: Excess borrowing as households don't internalize default risk

⇒ Slope of MC parameterizes the importance of these (and other) factors for pass-through

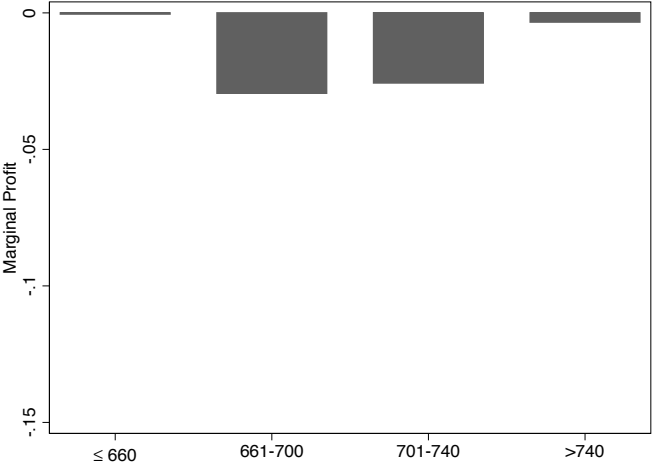
Estimating $MC'(CL)$

- Estimate $MC'(CL)$ using the same RDs with costs as outcome variable
 - Standard approach used in empirical insurance literature
 - Each experiment delivers two moments:
 1. Marginal costs at prevailing credit limit
 2. Average costs per dollar of credit limit
- ⇒ 2 moments allow us to identify two-parameter curve for marginal costs
- In paper: Linear marginal costs
 - Robust to other functional forms.

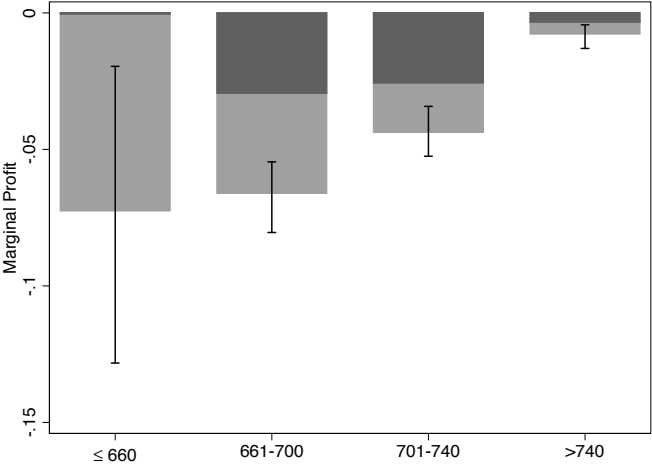
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- **Marginal Propensity to Lend**
 - Model
 - **Estimates**

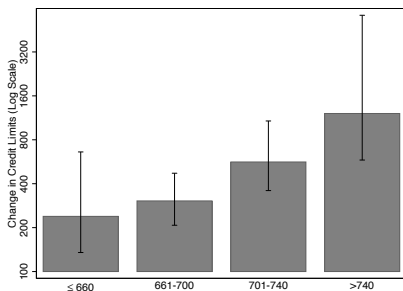
Marginal Profits at 48 Months



Impact of \$1K CL Increase on Marginal Profits



Marginal Propensity to Lend



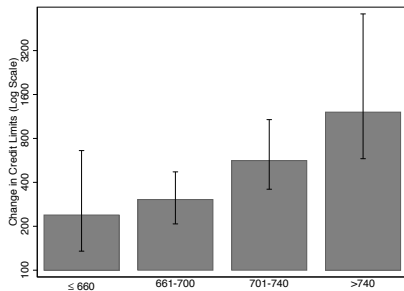
- Response to permanent 1 percentage point reduction in cost of funds:

$$MPL = -\frac{dCL}{dc} = -\frac{MPB}{MP'(CL)}$$

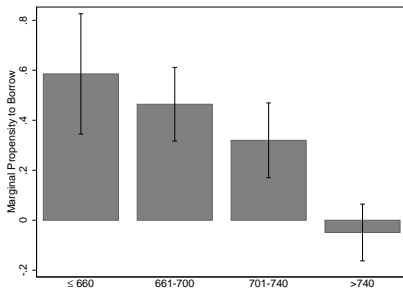
- FICO \leq 660: \$239
- FICO $>$ 740: \$1,211
- Fairly stable across time horizons

▶▶ Figure

MPL × MPB Takeaway



(a) MPL



(b) MPB Across All Accounts, 12 Months

- Suppose calculate effect as avg MPL across FICO \times avg MPB across FICO

\Rightarrow Accounting for correlation reduces effect by 49%

Contributions

1. Propose new framework to estimate strength of bank lending channel
 - Combine a simple model of lending with quasi-exogenous variation in contract terms to estimate sufficient statistics.
 - Overcomes time-series identification challenge.
2. Our approach to estimating MPL highlights importance of frictions such as asymmetric information in the bank-borrower interaction.
 - Complements literature that has focused on levels of bank capital.
3. Examine roles of credit supply vs. credit demand in constraining borrowing at the margin during the Great Recession.
 - Supply important for low FICOs, demand for high FICOs
 - Mismatch: Banks don't want to lend to those that want to borrow.
 - Similar mismatch likely in other credit markets.

Conclusion



Backup Slides

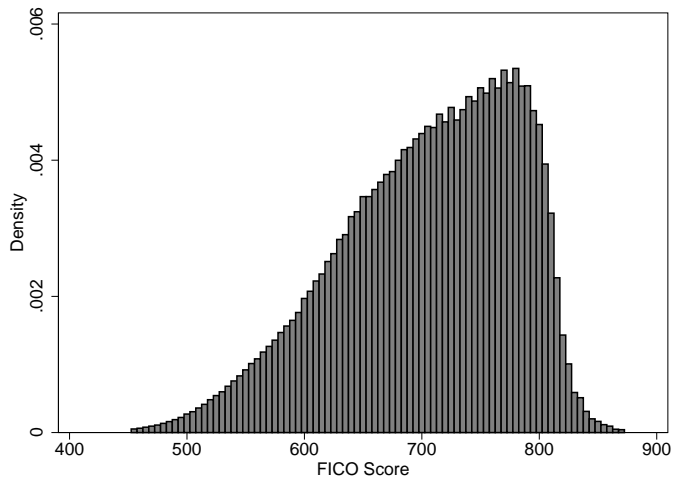
Focus of Program

Bush: "[TARP to] supply urgently needed money so banks and other financial institutions can avoid collapse and resume lending. [This rescue effort] will help American consumers and businesses get credit to meet their daily needs and create jobs."

ECB: Because the TLTROs will involve targeted lending, they will be tied to lending to euro-area non-financial corporations and households (excluding loans to households for house purchase).

The **Bank of England** and HM Treasury launched the Funding for Lending Scheme (FLS) in order to encourage lending to households and companies. The FLS offers funding to banks and building societies for an extended period. And it encourages them to supply more credit by making more and cheaper funding available if they lend more. Easier access to bank credit should boost consumption and investment by households and businesses.

FICO Score, Population Distribution



» Back to experiments

Summary Statistics, At Origination

	Average	S.D		Average	S.D
Credit Limit on Treated Card (\$)			Total Balances Across All Credit Card Accounts (\$)		
<i>Pooled</i>	5,265	2,045	<i>Pooled</i>	9,551	3,469
<i>≤660</i>	2,561	674	<i>≤660</i>	5,524	2,324
<i>661-700</i>	4,324	1,090	<i>661-700</i>	9,956	2,680
<i>701-740</i>	4,830	1,615	<i>701-740</i>	10,890	3,328
<i>>740</i>	6,941	1,623	<i>>740</i>	9,710	3,326
APR on Treated Card (%)			Credit Limit Across All Credit Card Accounts (\$)		
<i>Pooled</i>	15.38	3.70	<i>Pooled</i>	33,533	14,627
<i>≤660</i>	19.63	5.43	<i>≤660</i>	12,856	5,365
<i>661-700</i>	14.50	3.65	<i>661-700</i>	26,781	7,524
<i>701-740</i>	15.35	3.11	<i>701-740</i>	32,457	8,815
<i>>740</i>	14.70	2.52	<i>>740</i>	44,813	12,828

Statistics calculated on quasi-experiment-level dataset.

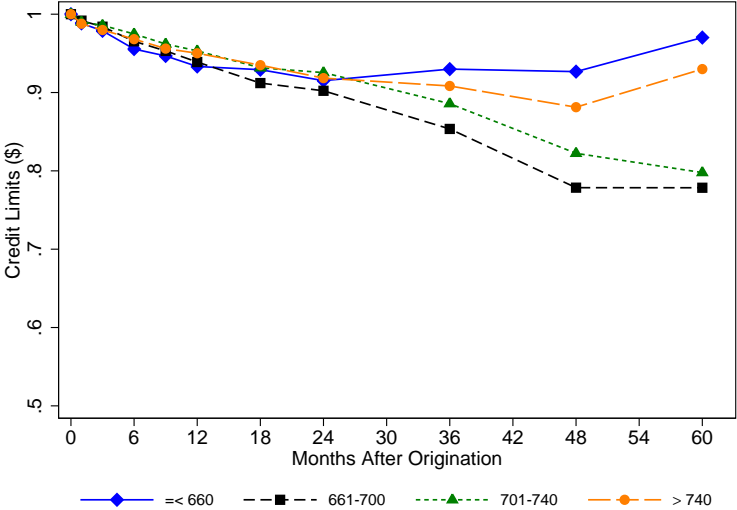
Summary Statistics, At Origination

	Average	S.D		Average	S.D
Number of Credit Card Accounts			Number Times 90+ DPD In Last 24 Months		
<i>Pooled</i>	11.00	2.93	<i>Pooled</i>	0.17	0.30
<i>≤660</i>	7.13	1.18	<i>≤660</i>	0.93	0.31
<i>661-700</i>	10.22	1.68	<i>661-700</i>	0.41	0.16
<i>701-740</i>	11.12	2.34	<i>701-740</i>	0.29	0.10
<i>>740</i>	12.63	2.92	<i>>740</i>	0.13	0.08
Age Oldest Account (Months)			Number Accounts Currently 90+DPD		
<i>Pooled</i>	190.1	29.1	<i>Pooled</i>	0.03	0.03
<i>≤660</i>	162.0	26.3	<i>≤660</i>	0.10	0.05
<i>661-700</i>	180.1	19.9	<i>661-700</i>	0.02	0.02
<i>701-740</i>	184.7	24.0	<i>701-740</i>	0.02	0.02
<i>>740</i>	208.6	25.7	<i>>740</i>	0.01	0.01

Statistics calculated on quasi-experiment-level dataset.

[▶▶ Back to experiments](#)

Persistence of Credit Limits



Persistence of Credit Limit Effect

	Months After Account Origination				
	12	24	36	48	60
<i>FICO</i>					
<i>≤660</i>	0.93 [0.91 , 0.96]	0.92 [0.87 , 0.96]	0.93 [0.87 , 0.99]	0.93 [0.83 , 1.03]	0.97 [0.83 , 1.17]
<i>661-700</i>	0.94 [0.92 , 0.95]	0.90 [0.87 , 0.92]	0.85 [0.81 , 0.88]	0.78 [0.7 , 0.85]	0.78 [0.66 , 0.93]
<i>701-740</i>	0.95 [0.94 , 0.97]	0.93 [0.9 , 0.95]	0.89 [0.85 , 0.91]	0.82 [0.75 , 0.88]	0.80 [0.68 , 0.91]
<i>>740</i>	0.95 [0.94 , 0.96]	0.92 [0.9 , 0.94]	0.91 [0.87 , 0.93]	0.88 [0.81 , 0.94]	0.93 [0.82 , 1.12]

» Back to distribution

Validity of Research Design

	Distribution of Jump Across Quasi-Experiments			Baseline
	Average	Median	Standard Deviation	
Credit Limit	1,472	1,282	796	5,265
APR (%)	0.017	-0.005	0.388	15.38
Months to Rate Change	0.027	0.016	0.800	13.37
Number of Credit Card Accounts	0.060	0.031	0.713	11.00
Total Credit Limit - All Accounts	151	28	2,791	33,533
Age Oldest Account (Months)	1.034	0.378	11.072	190.11
Number Times 90+ DPD - Last 24 Months	0.010	0.002	0.111	0.169
Number Accounts 90+ DPD - At Origination	0.001	0.001	0.017	0.026
Number Accounts 90+DPD - Ever	0.004	0.003	0.095	0.245
Number of Accounts Originated	10.21	4.38	47.61	580.12

» Back to RD specification

Details on Implementation

For each experiment, run second-order local polynomial regression.

$$\min_{\alpha_{y,D}, \beta_{y,D}, \gamma_{y,D}} \sum_{i \in \mathbb{I}} \left[y_i - \alpha_{y,D} - \beta_{y,D}(x_i - \bar{x}) - \gamma_{y,D}(x_i - \bar{x})^2 \right]^2 K \left(\frac{x_i - \bar{x}}{h} \right)$$

Use triangular kernel: $K \left(\frac{x_i - \bar{x}}{h} \right)$.

$$\tau = \frac{\hat{\alpha}_{\text{Outcome},H} - \hat{\alpha}_{\text{Outcome},L}}{\hat{\alpha}_{\text{Credit Limit},H} - \hat{\alpha}_{\text{Credit Limit},L}}.$$

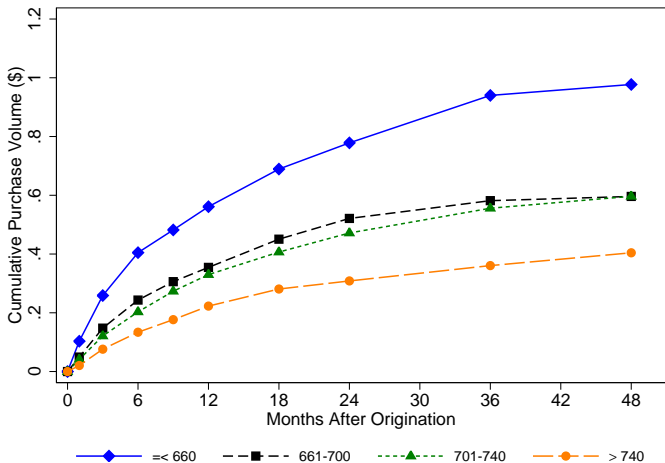
► Back to Research Design

Summary Statistics, Post Origination

	FICO Score Group				FICO Score Group				
	≤660	661-700	701-740	>740	≤660	661-700	701-740	>740	
Credit Limit (\$)					Total Balances Across All Cards (\$)				
<i>After 12 Months</i>	2,652	4,370	4,964	6,980	<i>After 12 Months</i>	6,155	10,546	11,411	10,528
<i>After 24 Months</i>	2,414	4,306	4,946	7,071	<i>After 24 Months</i>	5,919	10,521	11,307	10,703
<i>After 36 Months</i>	2,301	4,622	5,047	7,005	<i>After 36 Months</i>	6,387	10,716	11,702	11,267
<i>After 48 Months</i>	2,252	4,525	4,985	6,944	<i>After 48 Months</i>	6,698	10,437	11,665	11,137
<i>After 60 Months</i>	2,290	4,449	4,601	6,839	<i>After 60 Months</i>	7,566	10,591	11,972	12,490
ADB (\$)					Cumulative Purchase Volume (\$)				
<i>After 12 Months</i>	1,260	2,160	2,197	2,101	<i>After 12 Months</i>	2,679	2,579	2,514	2,943
<i>After 24 Months</i>	1,065	1,794	1,719	1,524	<i>After 24 Months</i>	3,583	3,966	3,910	4,653
<i>After 36 Months</i>	1,164	1,734	1,481	1,343	<i>After 36 Months</i>	3,987	4,834	4,724	5,525
<i>After 48 Months</i>	1,079	1,501	1,260	1,064	<i>After 48 Months</i>	4,223	5,253	5,162	5,897
<i>After 60 Months</i>	1,050	1,465	1,097	1,084	<i>After 60 Months</i>	4,390	5,509	5,424	6,095

» Back

MPS Heterogeneity (Cumulative Purchase Volume)



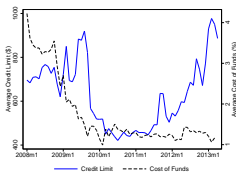
- Own-card effect due to additional spending, not slower pay-down of debt.
- BUT: Do not have good measure of total spending ...

MPS Heterogeneity

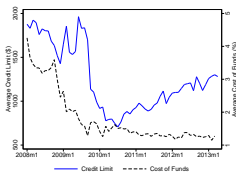
	Months After Account Origination				
	12	24	36	48	60
Panel C: Cumulative Purchase Volume					
<i>FICO</i>					
<i>≤660</i>	0.56 [0.49, 0.66]	0.78 [0.64, 0.95]	0.94 [0.75, 1.14]	0.98 [0.78, 1.2]	0.99 [0.79, 1.21]
<i>661-700</i>	0.35 [0.31, 0.4]	0.52 [0.45, 0.6]	0.58 [0.49, 0.68]	0.60 [0.5, 0.7]	0.62 [0.51, 0.73]
<i>701-740</i>	0.33 [0.28, 0.38]	0.47 [0.4, 0.54]	0.56 [0.46, 0.63]	0.60 [0.5, 0.68]	0.60 [0.5, 0.7]
<i>>740</i>	0.22 [0.19, 0.26]	0.31 [0.25, 0.37]	0.36 [0.27, 0.44]	0.40 [0.32, 0.49]	0.44 [0.34, 0.54]

» Back to MPB

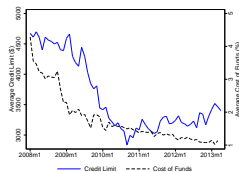
Credit Limits and Cost of Funds in Time Series



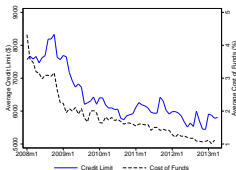
(a) FICO ≤ 620



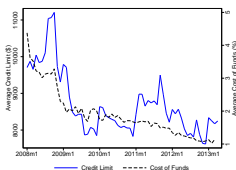
(b) 621 - 660



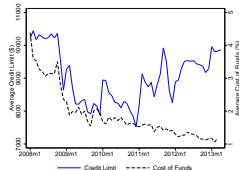
(c) 661-720



(d) 721-760

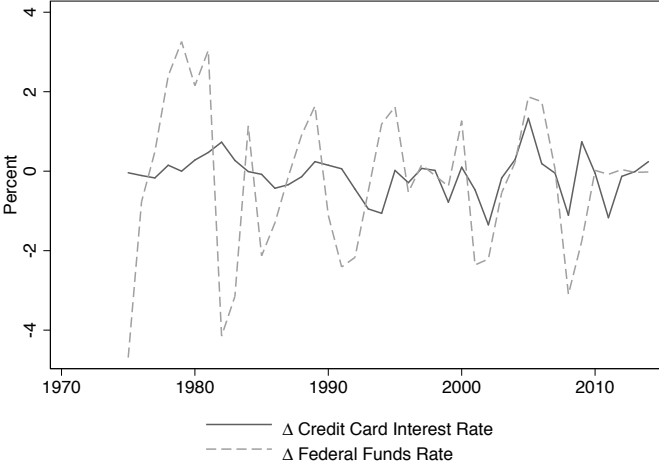


(e) 762-800



(f) FICO > 800

Credit Card Interest Rates vs. Federal Funds Rate



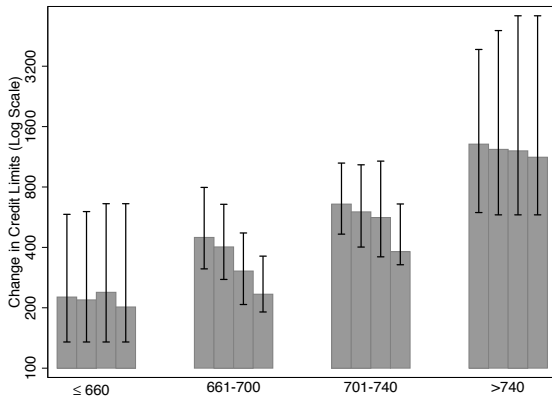
▶ Back to margin of adjustment

Summary Statistics, Post Origination

	FICO Score Group					FICO Score Group			
	≤660	661-700	701-740	>740		≤660	661-700	701-740	>740
Cumulative Total Costs (\$)					Cumulative Total Revenue (\$)				
<i>After 12 Months</i>	122	172	169	147	<i>After 12 Months</i>	233	192	181	175
<i>After 24 Months</i>	281	451	433	304	<i>After 24 Months</i>	474	503	439	347
<i>After 36 Months</i>	459	710	644	395	<i>After 36 Months</i>	740	793	663	449
<i>After 48 Months</i>	588	845	808	488	<i>After 48 Months</i>	953	971	863	563
Cumulative Chargeoffs (\$)					Cumulative Interest Charge Revenue (\$)				
<i>After 12 Months</i>	47	67	61	35	<i>After 12 Months</i>	106	61	52	42
<i>After 24 Months</i>	178	259	245	124	<i>After 24 Months</i>	297	295	243	159
<i>After 36 Months</i>	306	443	403	190	<i>After 36 Months</i>	484	520	420	243
<i>After 48 Months</i>	403	552	524	261	<i>After 48 Months</i>	625	669	578	340
Cumulative Prob 60+ DPD (\$)					Cumulative Fee Revenue (\$)				
<i>After 12 Months</i>	6.4%	4.1%	3.6%	1.6%	<i>After 12 Months</i>	73	79	79	74
<i>After 24 Months</i>	12.0%	9.3%	8.2%	3.8%	<i>After 24 Months</i>	129	129	121	101
<i>After 36 Months</i>	15.1%	12.2%	10.9%	5.2%	<i>After 36 Months</i>	192	173	157	116
<i>After 48 Months</i>	16.5%	13.6%	12.2%	5.9%	<i>After 48 Months</i>	254	199	187	126
Cumulative Cost of Funds (\$)					Cumulative Profits (\$)				
<i>After 12 Months</i>	14	16	16	15	<i>After 12 Months</i>	111	21	12	30
<i>After 24 Months</i>	23	29	28	25	<i>After 24 Months</i>	194	56	9	46
<i>After 36 Months</i>	28	38	36	31	<i>After 36 Months</i>	281	91	23	59
<i>After 48 Months</i>	31	43	41	34	<i>After 48 Months</i>	365	126	55	75

» Back to default

MPL at 12 to 48 Month Time Horizons



» Back to MPL