

Unraveling Consumer Credit Markets

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One Slide Summary

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- How & why did the US credit cards market unravel. Why not other credit markets?

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Contributions:

- Study an unraveling in information sharing due to innovation (Trended Data).
- Unravel how profitability depends on multiple sources of information asymmetry.
- Adverse selection of information sharing.
- New empirical insights on credit markets
(distribution & predictability of consumer behaviors driving realized profitability).

Credit Cards Explained

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$t = 1$:

- \$1,000 new spending (\rightarrow generates \$5 net interchange revenue)
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- \$12 interest + \$15.00 fee = \$27 financing charges
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- \$2,777 statement balance & \$55 minimum payment due

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$$\text{spending}_t = \text{balance}_t - \text{balance}_{t-1} + \text{repayment}_t - \text{fincharge}_t$$

$$\text{debt}_t = \text{balance}_{t-1} - \text{repayment}_t$$

Credit Card Profitability Uncertain: Multiple Information Asymmetry & Revenue Streams

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Credit cards have multiple revenue streams.

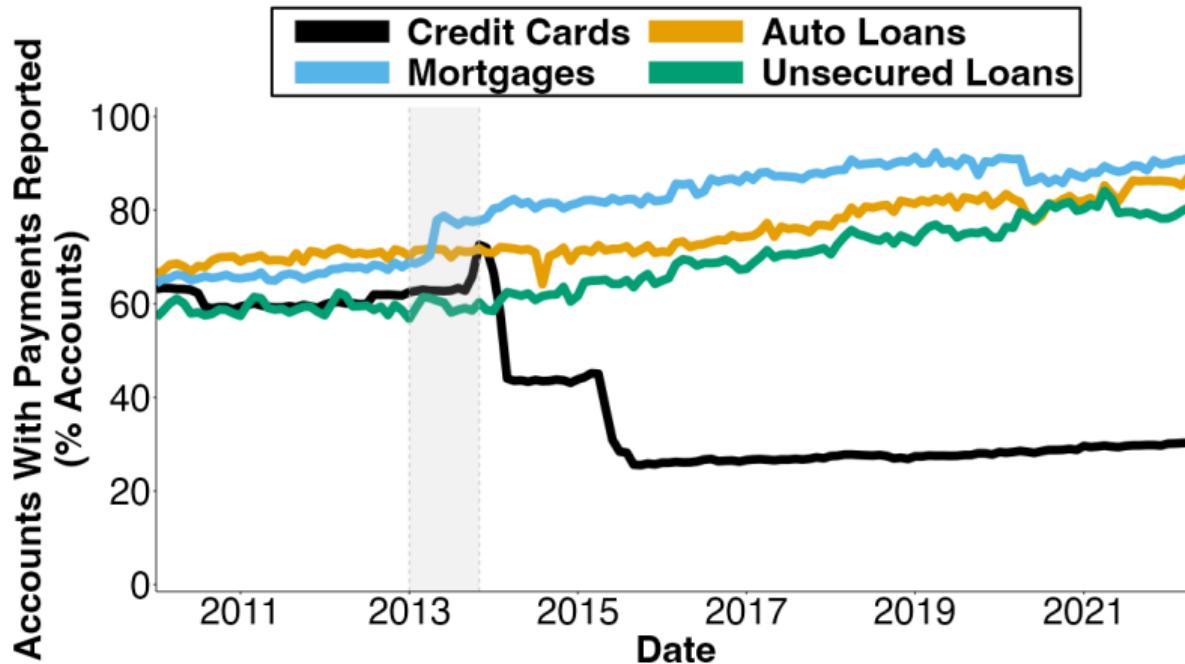
Profitability ultimately depends on ex-post consumer behaviors:

- Revolving debt amount & duration → interest income
- Defaults → charge-offs
- Late fees (Agarwal et al., 15 QJE; Nelson, 22 WP)
- Spending → interchange income.

If repayment_t unobserved, do not know spending_t or debt_t

Will model profitability ft. new methodology estimating fincharge_t

Unraveling in Credit Card Reporting of repayments amounts to US Credit Bureau



Seminal theory (Pagano & Jappelli, 93 JF) would predict ↑ sharing.

Core economics & finance at heart of this research

Economically Large Event in Macroeconomically Important Markets:

- US credit card market
 - 70% (180 mn) people & \$825bn balances (CFPB, 2021)
- US credit information market
 - 90% people have credit file (CFPB, 2021)

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Relevant Literatures:

- **Informational Economics (Information Asymmetries, Selection Markets)**
(e.g. Akerlof, 70; Jaffee & Russell, 76; Rothschild & Stiglitz, 76; Stiglitz & Weiss, 81)
- **(Credit) Market Design & Innovation**
(e.g. Pagano & Jappelli, 93; Padilla & Pagano, 00)
- **Household Finance**

Topic of policy relevance: US consumer financial protection bureau (CFPB) launched investigation in May 2022

 Consumer Financial Protection Bureau

Search

[Blog](#)

CFPB tells credit card CEOs: Practice of suppressing payment data has potential for consumer harm

By John McNamara - MAY 25, 2022

Innovation

'Core / Non-Payment Data'

- statement balance
- minimum payment due
- default status
- credit limit
- opening date

Actual repayments unraveled.

Installment loans (e.g. auto loans, mortgages, unsecured loans) also show:

- origination amount
- scheduled term

Can recover interest rates (e.g. Shahidinejad, 22 WP; Yannelis & Zhang, 22 WP).

Credit Bureaus Created Innovation in 2013: “Trended Data”

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July 2, 2020

What is Trended Data and Why Should I Care?

News

PERSONAL BUSINESS PUBLIC SECTOR

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How trended credit data and alternative data are like a scrapbook

Trended Data reveals consumer heterogeneity - *especially* for credit cards

Traditional credit reports create point-in-time variables
(e.g. current balance, any default in last 7 years).

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Trended Data creates variables using credit reports over time (trends!)
– especially combining payments data with balances.

- Reveals **credit cards** behaviors
driving profitability beyond default.

- Revolving debt.
- New spending.
- Interest rates.

Premium Algorithms

Understand key consumer behavior patterns such as revolving credit, balance build, loyalty and product preference to enhance strategies



Reveals *not just* credit risk but *who* profitable consumers are.

Predicting Profitability

How Predictable is Consumer Behavior?

Firm's problem is predicting profitable types to target marketing to.

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Models:

1. Credit Score (100 groups)
2. Credit Score + Non-Payment (e.g. credit limit, statement balances, utilization, default)
3. Credit Score + Non-Payment + Payment (e.g. spending, revolving debt)

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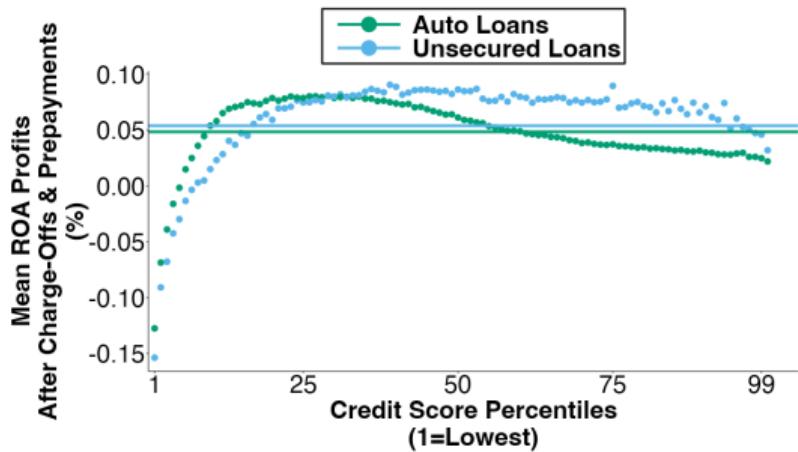
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Comparing Model 2 to Model 3 shows informational value of
Trended Data harnessing payments data (to target profitable consumers).

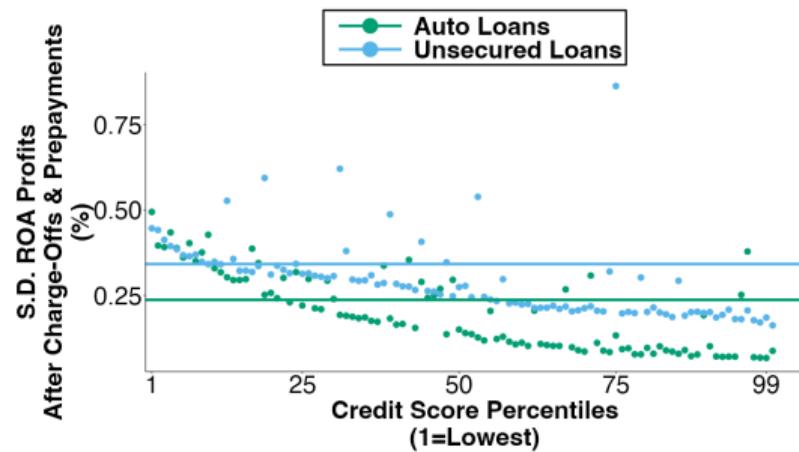
Use data to December 2012 to predict outcomes.

Installment Loan Ex-Post Profits

Mean



S.D.



$$ROA = \frac{\Pi}{A} = \frac{(TCC \times \frac{T}{N}) - C}{A}$$

where ROA is Return on Assets, A is loan principal, Π is ex-post realized profits,
 TCC is total cost of credit, C is charge-offs,
 T is actual loan months (restrict to $T \leq N$), N is scheduled loan months.

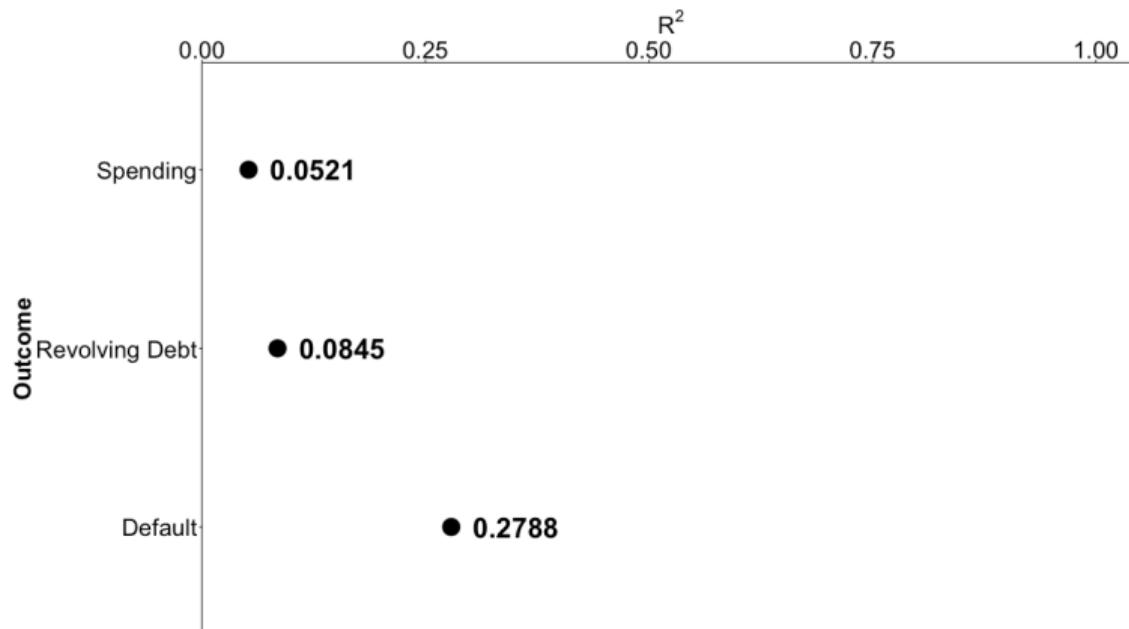
Predictability of Installment Loan Ex-Post Profits

Despite auto loans and unsecured loans having different product & profitability structures, results consistent:

'Actual payment' amount does little to improve prediction of post-origination behaviors (charge-offs, prepayment) and so does not help targeting of profitable consumers.

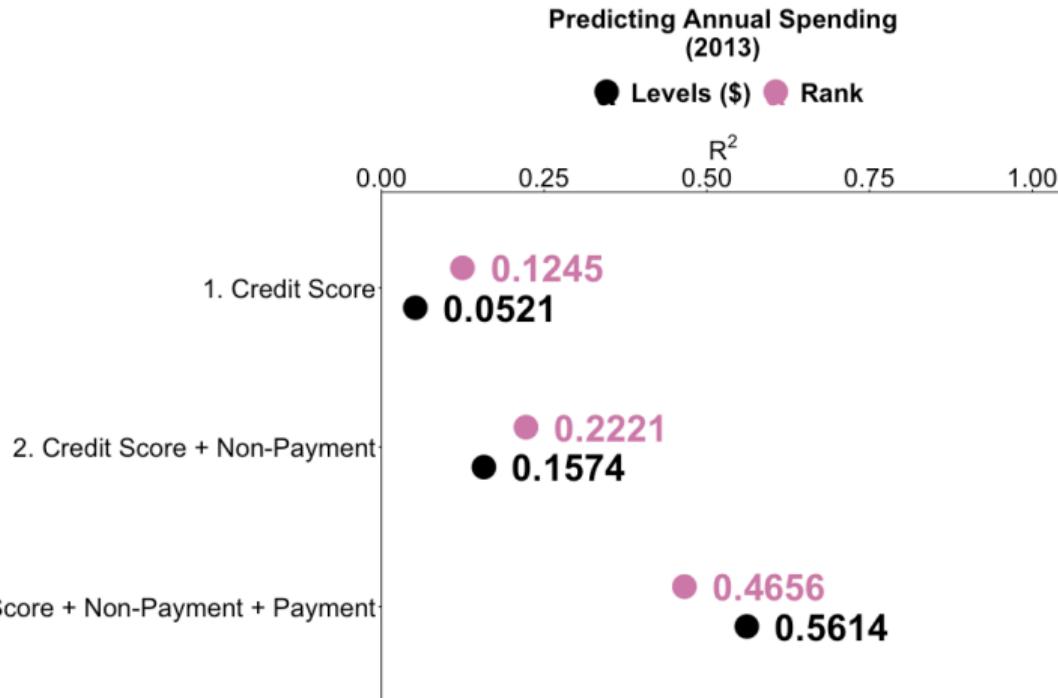
Model	R^2 Predicting Profits (\$) After Charge-Offs & Prepayments	
	Auto Loans	Unsecured Loans
1. Credit Score	0.019	0.014
2. Credit Score + Core Variables	0.376	0.952
3. Credit Score + Core Variables + Actual Payment	0.382	0.954

Credit Scores Alone Poor Predictor of Spending & Revolving Debt



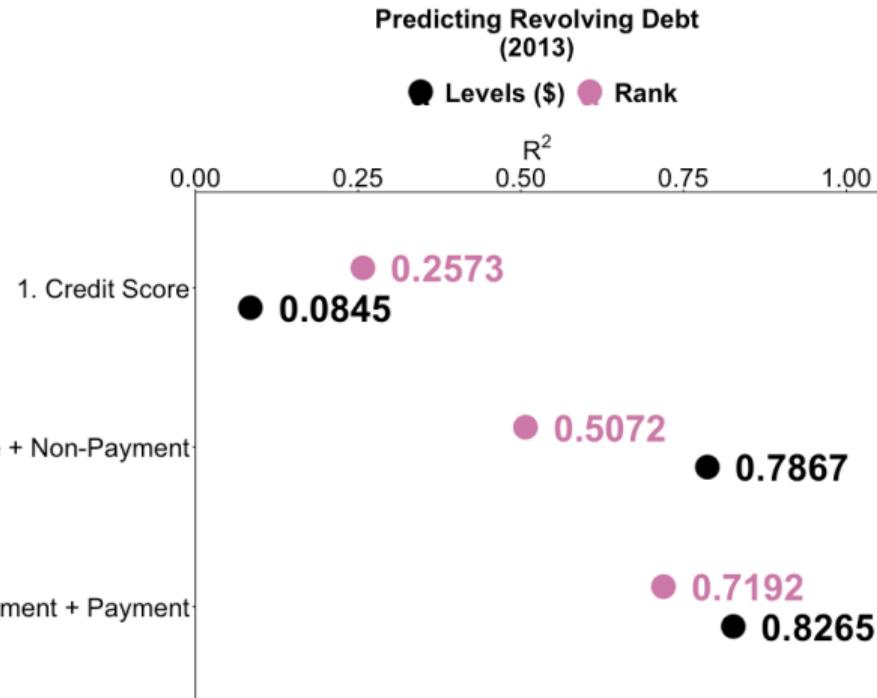
Predicting Profitability: Spending

Prediction models
(2012 data, OLS)



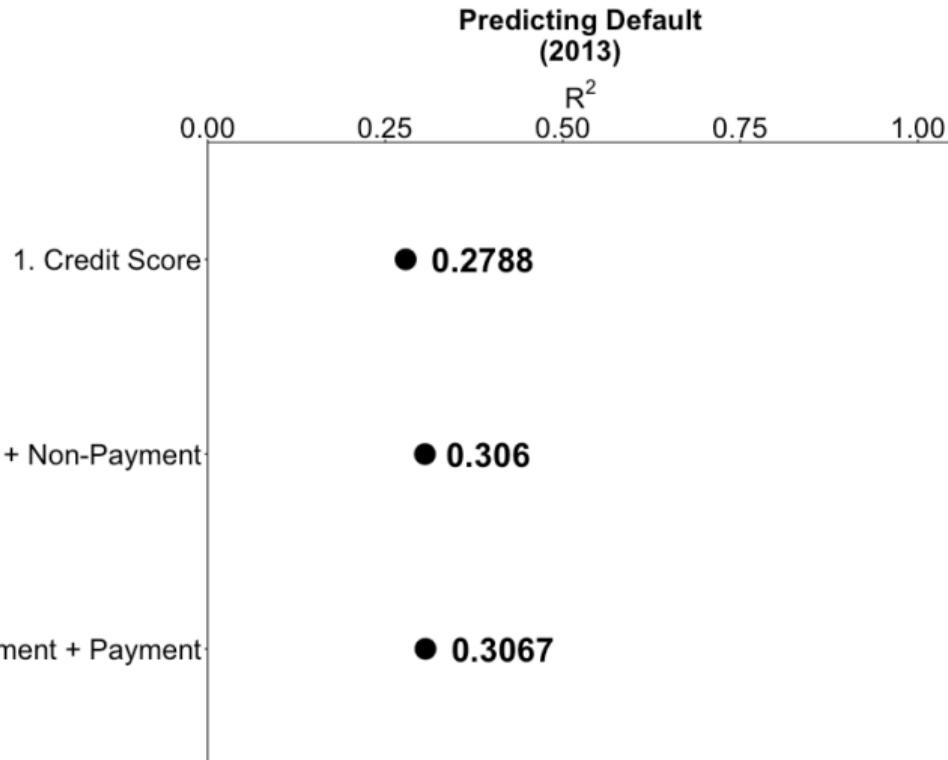
Predicting Profitability: Revolving Debt

Prediction models
(2012 data, OLS)



Predicting Profitability: Default

Prediction models
(2012 data, OLS)



New Methodology for Measuring Credit Card Financing Charges

Minimum payment (M_t) are calculated deterministically by formula such as:

$$M_t = \max\{\$D, I\% \text{balance}_t + \text{interest}_t + \text{fees}_t\}$$

e.g. Chase:

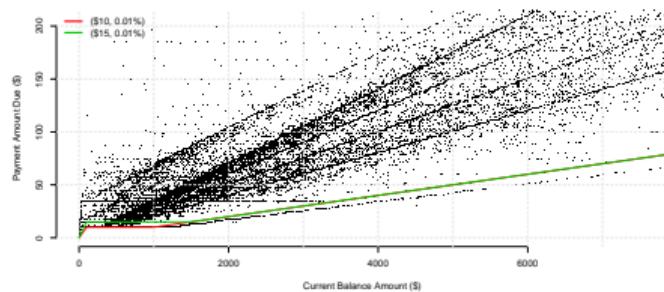
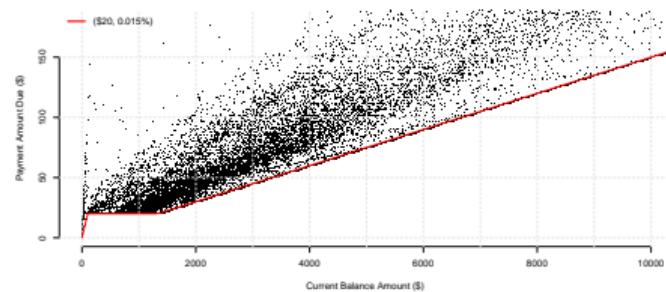
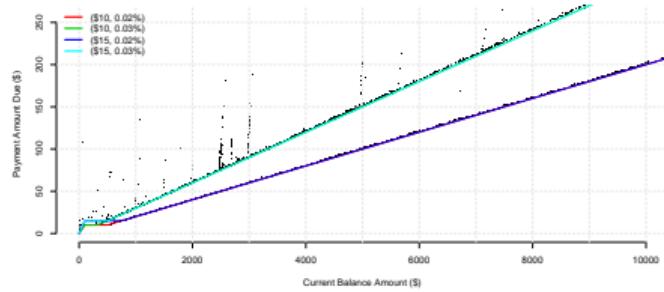
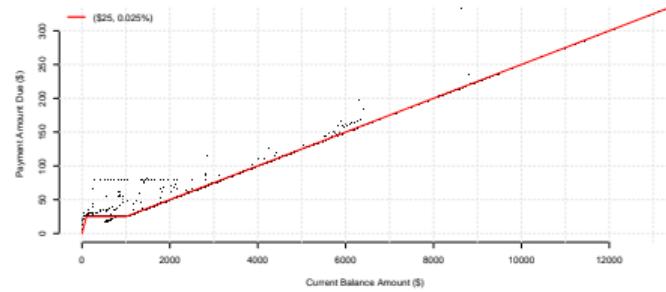
Minimum Payment: We will calculate the minimum payment as the larger of: 1) \$25 (or total amount you owe if less than \$25); or 2) the sum of 1% of the new balance, the periodic interest charges, and late fees we have billed you on the statement for which your minimum payment is calculated.

With enough data you can back out D and I .

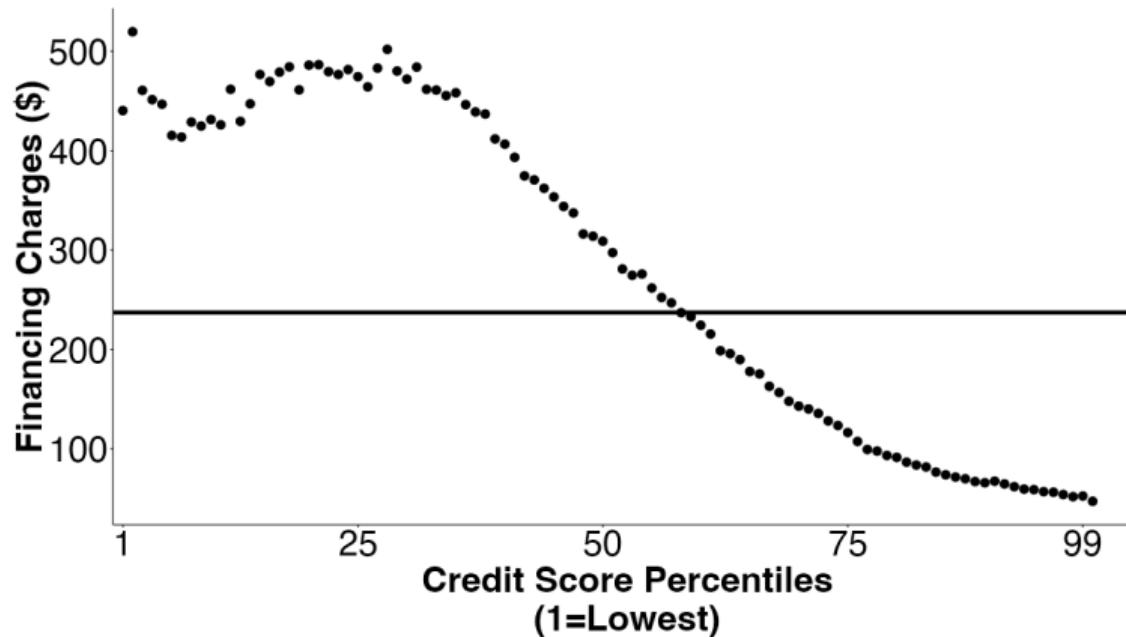
Do lender-by-lender for transacting months to remove noise. Using CFPB public agreements to guide candidate parameters.

If know minimum payment rule *then* difference between *observed* minimum payment and *predicted* minimum payment is financing charges.

4 Examples



2013 Financing Charge Estimates

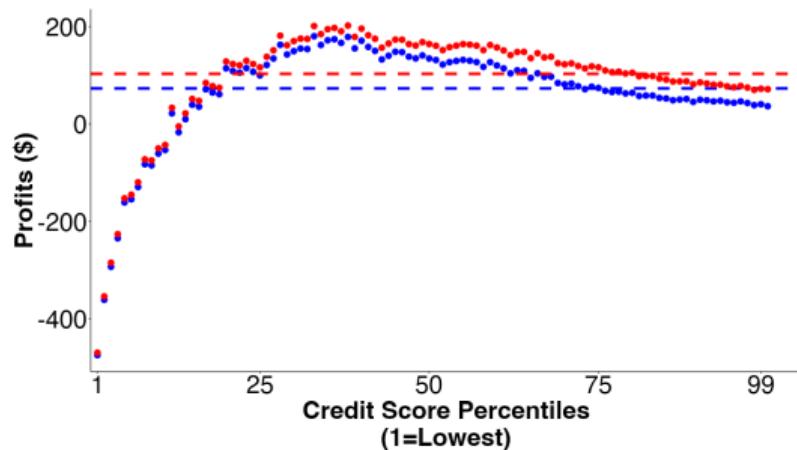


Broadly consistent with Agarwal et al. (15 QJE, 22 WP) using confidential OCC & Fed data.

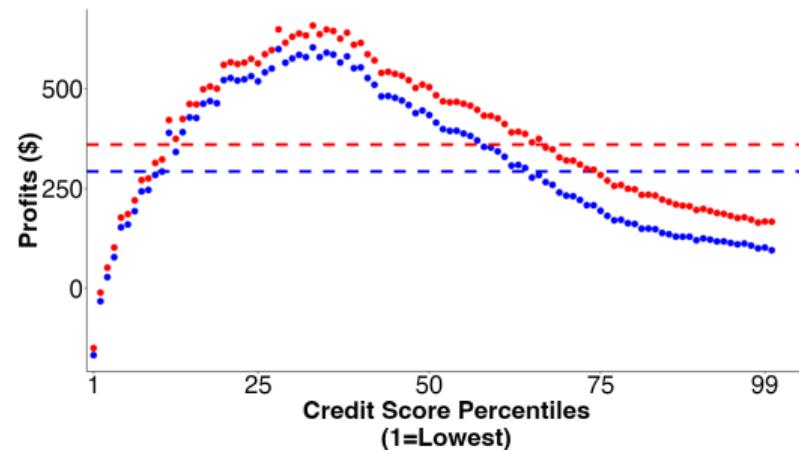
Profits before and after interchange

$$\Pi_i = \text{fincharge}_{i,2013} + \text{interchange}_{i,2013} - \text{chargeoff}_{i,2022}$$

2013



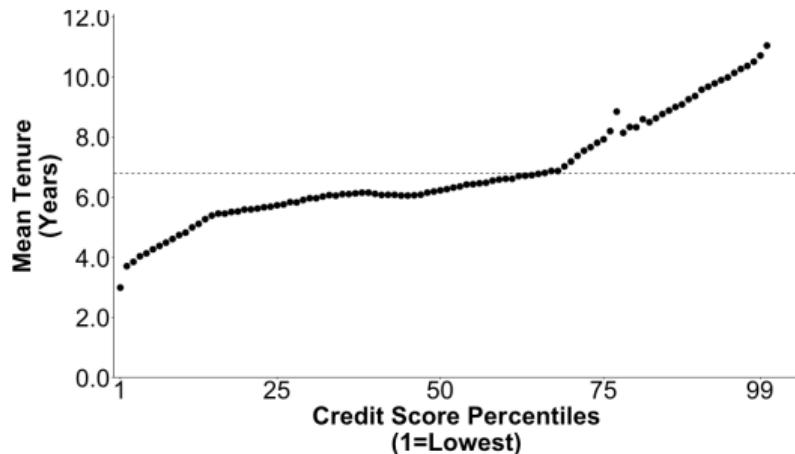
2012 - 2013



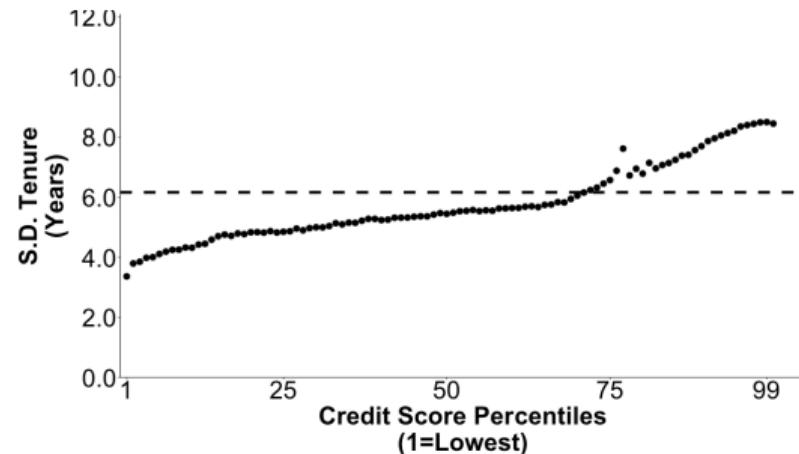
Work-in-progress on tails, estimating EAPR, prediction, charge-offs.

N.b. High Credit Score Cards Much Longer Tenure

Mean



S.D.



Work-in-progress adjusting for *lifetime* profitability.

Credit Card Lender Heterogeneity

Unraveling Driven By Some Credit Card Lenders **Stopping** Reporting



Always: Share payments data in 2012 & by 2015.

Stoppers: Share payments data in 2012 but not by 2015.

Never: Never share payments data in 2012 & by 2015.

Others: Everyone else.

Adverse Selection in Reporting Repayments

	Always	Stoppers	Nevers
Credit Score	710.6	711.5	736.6
(S.D.)	(89.8)	(91.8)	(79.4)
Tenure Years	6.21	8.15	12.44
(S.D.)	(6.81)	(6.87)	(9.87)
Credit Limit	8,768	9,679	10,888
(S.D.)	(7,951)	(9,724)	(10,420)
Statement Balance	2,288	2,586	2,859
(S.D.)	(3,606)	(4,061)	(4,827)
Utilization	41.95	43.98	34.38
(S.D.)	(35.24)	(34.99)	(31.91)
Cards	50 mn	131 mn	90 mn

Always < Stoppers < Nevers in mean credit scores.

Always < Stoppers < Nevers in mean & variance tenure, limits, & balances.

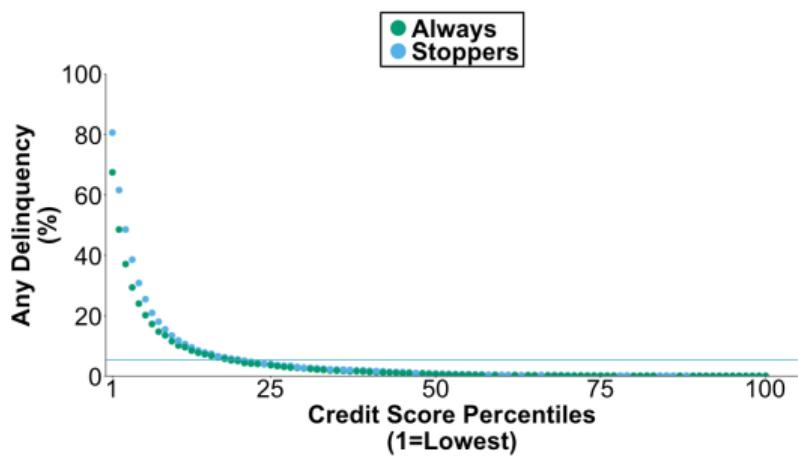
Reporting Repayments Data is Monotonic in Tenure, Credit Limit & Statement Balance (All Residual of Credit Score)

	Always	Stoppers	Nevers
Tenure Years	-2.59	-0.70	2.92
(S.D.)	(6.48)	(6.56)	(9.51)
Credit Limit	-383	448	609
(S.D.)	(6,850)	(8,570)	(10,148)
Statement Balance	-310	18	422
(S.D.)	(3,487)	(3,949)	(4,659)
Utilization	-1.16	1.30	-1.33
(S.D.)	(22.47)	(22.93)	(22.80)
Cards	50 mn	131 mn	90 mn

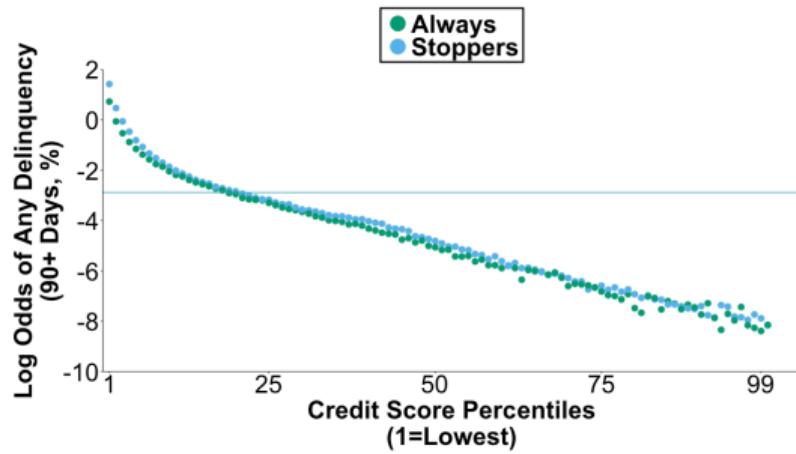
Always < Stoppers < Nevers in mean & variance tenure, limits, & balances.

Always & Stoppers Have Similar Default Rates Conditional on Credit Score.

Mean

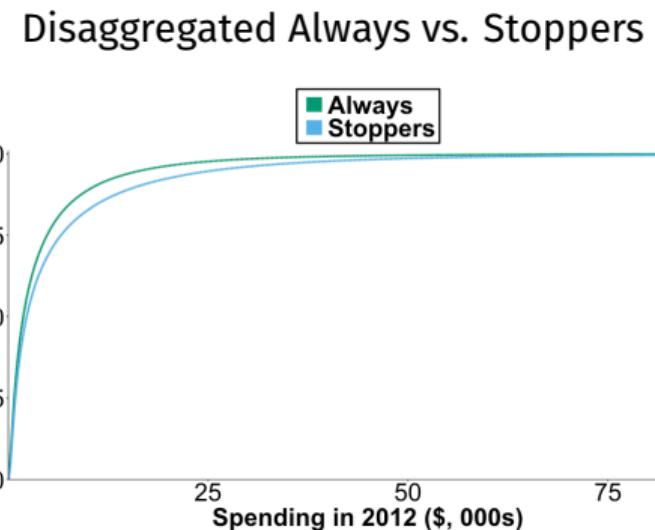
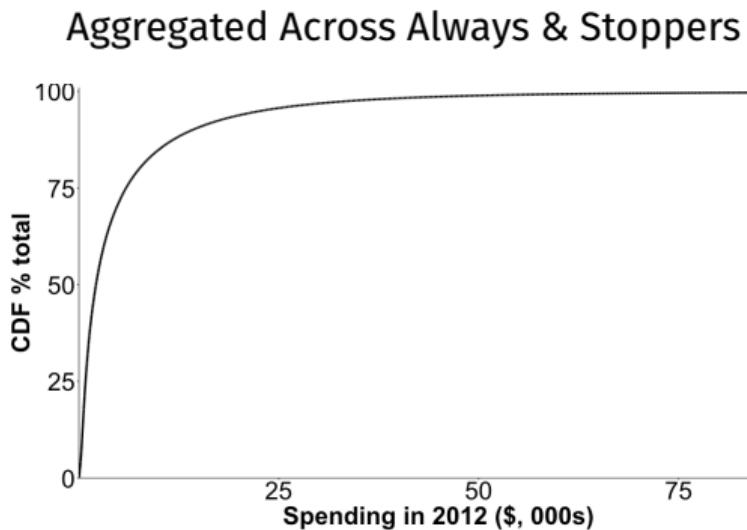


Log Odds

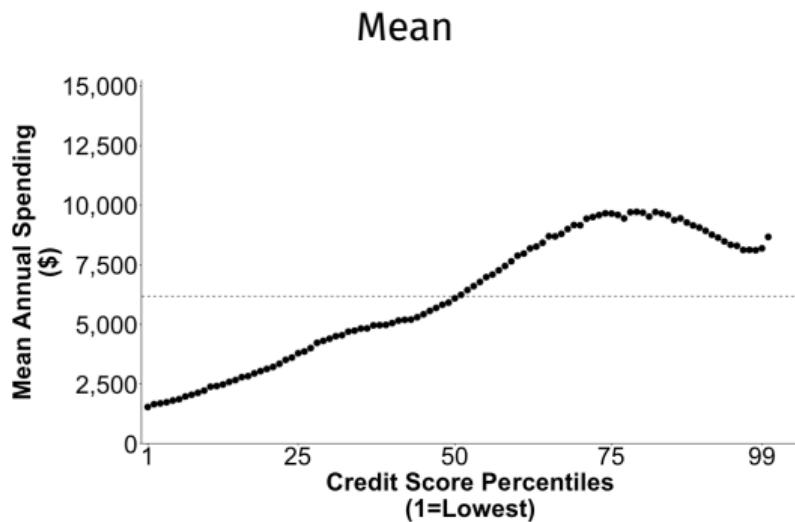


Credit risk doesn't appear to be main reason for differential reporting.

Large Variation in Spending.

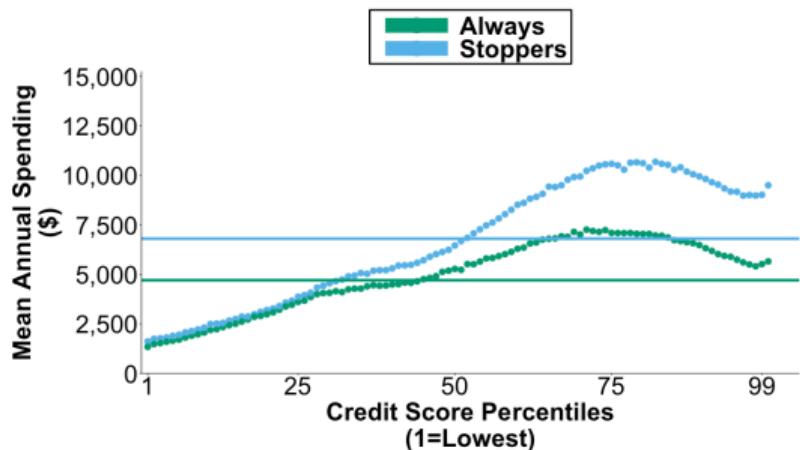


Large Variation in Spending Conditional on Credit Score.

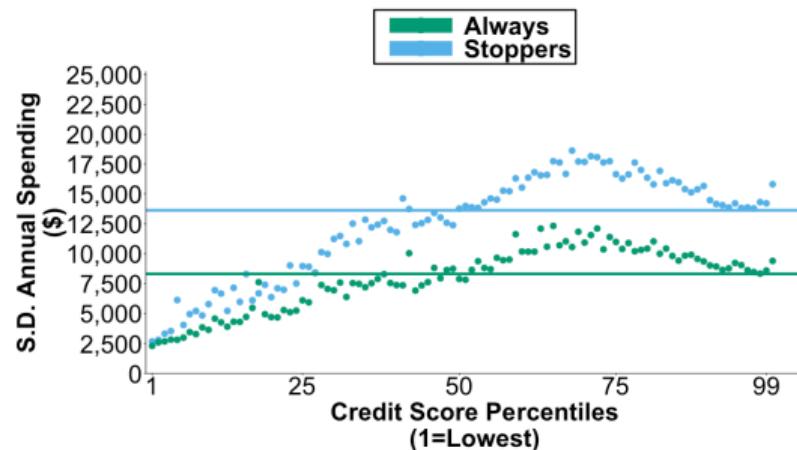


Adverse Selection - Stoppers spend more than Always

Mean



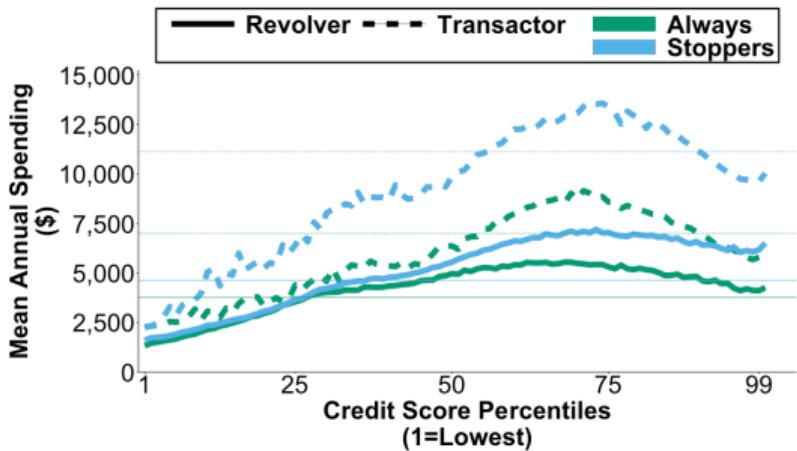
S.D.



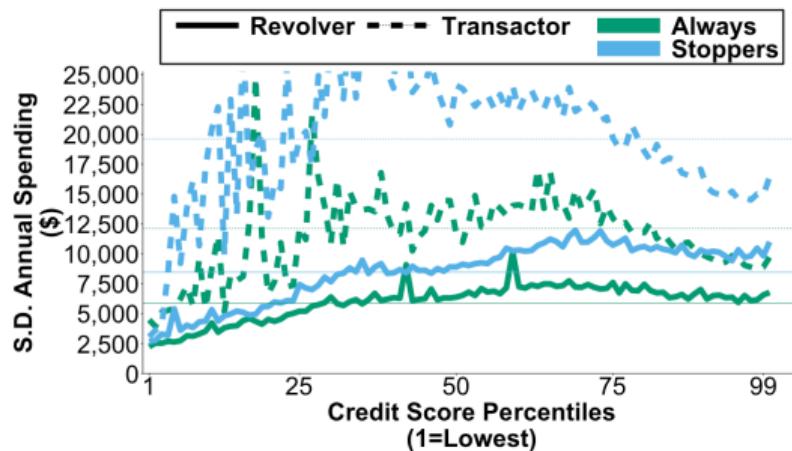
Stoppers higher mean and variance than Always.

Larger differences when decompose transactors vs. revolvers: Stoppers spend more than Always

Mean



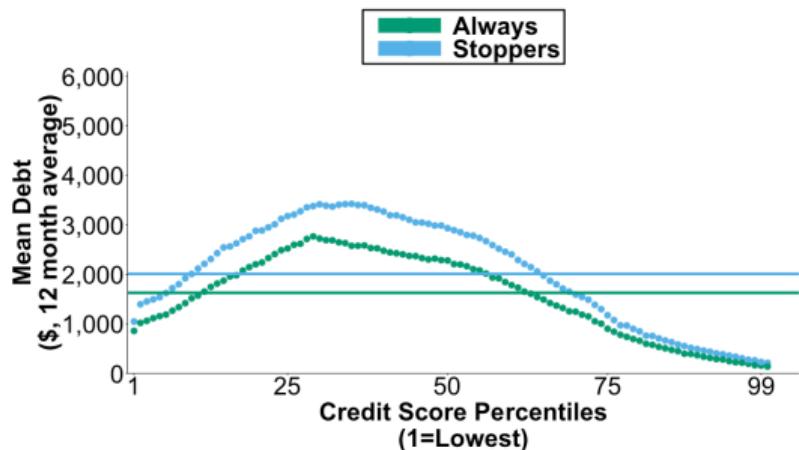
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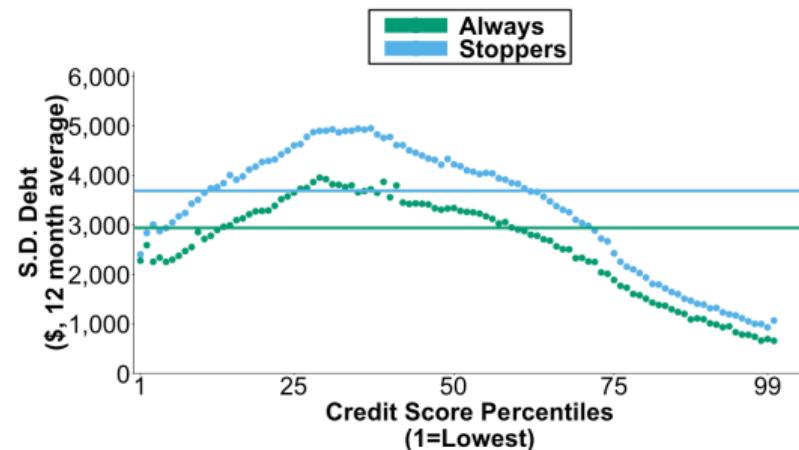
Stoppers higher mean and variance than Always.

Adverse Selection - Stoppers revolve more debt than Always

Mean



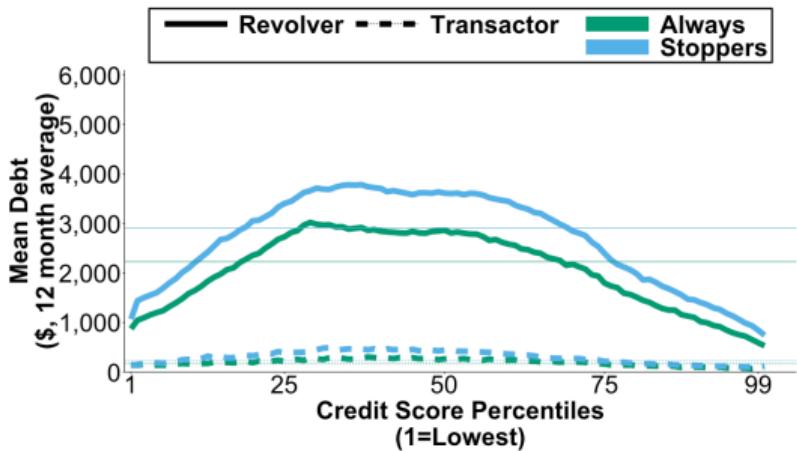
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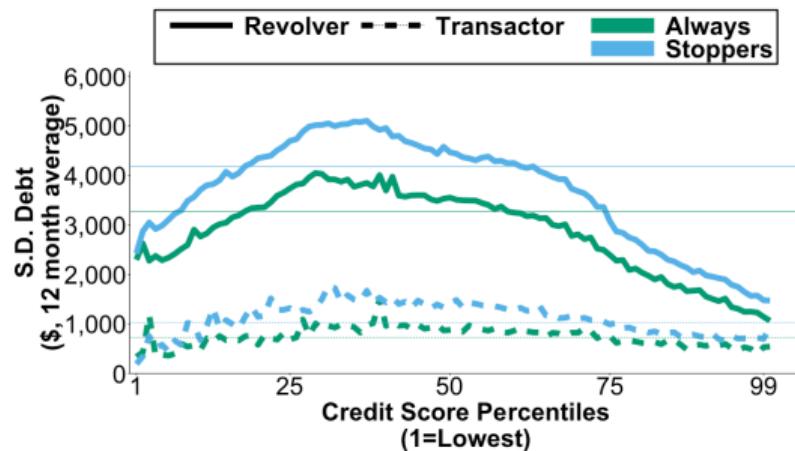
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Stoppers higher mean and variance than Always.

Predicting **Stoppers** Credit Card Behaviors By Training Model Using **Always** Data Performs Poorly

Post-2015 credit bureaus only observe payments data for **Always** lenders.

Evaluate how models trained on **Always** perform out-of-sample for **Stoppers**.

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Evaluate how models trained on **Always** perform out-of-sample for **Stoppers**.

Performs poorly:

- Predicting 2013 Spending:
 $R^2 = 0.175$ out-of-sample for **Stoppers**
(vs. 0.458 in-sample for **Always**).

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Performs poorly:

- Predicting 2013 Spending:

$R^2 = 0.175$ out-of-sample for **Stoppers**
(vs. 0.458 in-sample for **Always**).

- Predicting 2013 Revolving Debt:

$R^2 = 0.479$ for **Stoppers**
(vs. 0.724 in-sample for **Always**).

Predicting Lenders Stopping Reporting

Take Always or Stoppers 2012 to 2015 with 100,000+ credit cards. One observation per firm (N = 53).

$$Pr(Reporting_{f,2015} = 1) = \alpha + X'\beta + \varepsilon_{f,2012}$$

If X only includes means:

$$R^2 = 0.044$$

If X includes means and s.d.:

$$R^2 = 0.457$$

X variables: credit score, tenure, credit limit, statement balance, utilization.

N.b. also heterogeneity across firms.

Conclusions

Interim Conclusions

- Unraveling driven by innovation (Trended Data) enhancing profitability prediction.
- Unraveling due to multiple sources of information asymmetry (spending & revolving debt) beyond credit risk.
- Credit card market – and especially subset of lenders – most affected: large dispersion in profitability & predictability.
- Large unraveling in credit cards and not installment-based credit products (e.g. autos, mortgages) where less information asymmetry beyond credit risk & innovation less disruptive.
- Lenders most affected stopped reporting data input (payments data) innovation relied on to foreclose on competitors.
- Requiring firms to report data improves market efficiency (based on credit limit reporting).

Thank you!



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[@gk_ben](https://twitter.com/gk_ben)

Appendix

Trade-offs of sharing data non-reciprocally

Benefits of Sharing

1. Technology
2. Reduce Information Asymmetries

Costs of Sharing

1. Short-Run Poaching
2. Long-Run Increased Competition

Technological reasons explain potential benefits of sharing data non-reciprocally

Technological benefits may be irrespective of whether competitors share.

1. Unobserved Efficiencies Processing Data

(Not Adding Value to Data)

- Not testable in data.

2. Improved Credit Risk Scoring

(Adding Value to Data)

- Testable in data building predictive model.

3. Improved Customer Acquisition Targeting

(Adding Value to Data for Non-Credit Risk Reasons)

- Testable in data building predictive model.

Economic reasons for understanding which firms never/stop/always share data

- **Firm Differentiation:** Firms more different (e.g. more loyal customers, more focused on a profitable subsegment), less likely to share.
 - Testable in data comparing consumer bases (e.g. card tenures).
- **Multi-Homing:** Firms where consumers hold other cards, more likely to share.
 - Testable in data comparing lender's wallet share and showing predictive value-add of merging with competitors' data.
- **Economies of Scale (Diseconomies also possible reason):** Smaller firms have higher fixed costs, more likely to share to outsource.
 - Testable in data comparing firm sizes.

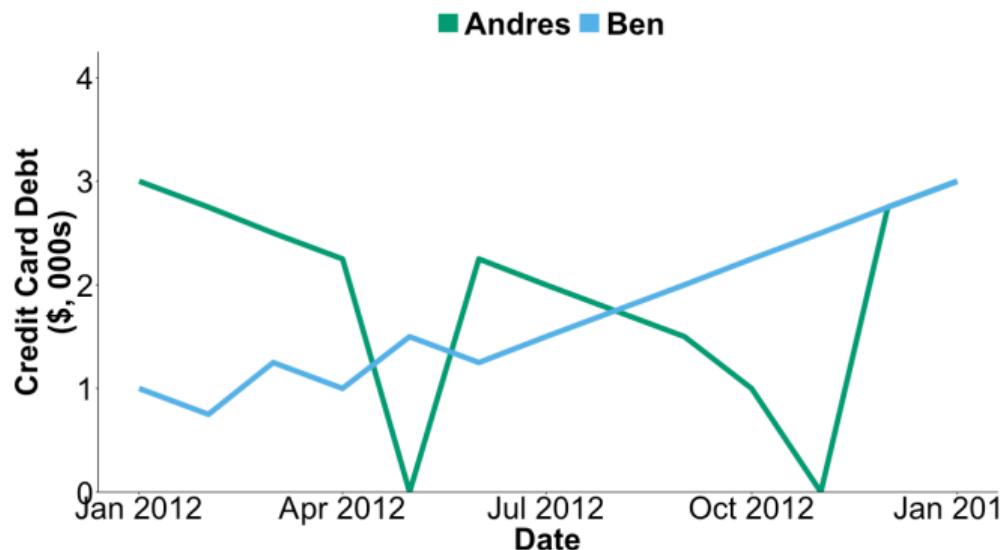
Working hypothesis is firms holding informational market power never/stop sharing to foreclose on rivals.

What is “Trended Data”?

Trended Data uses up to 30 months of data:

- Trends in balances, credit utilization, payments.

Example: Jan 2013 (**Avocado**) Andrés & (**Blue**) Ben same credit card debt but...
Trended Data reveals **Andrés** repays their debt unlike **Ben**.

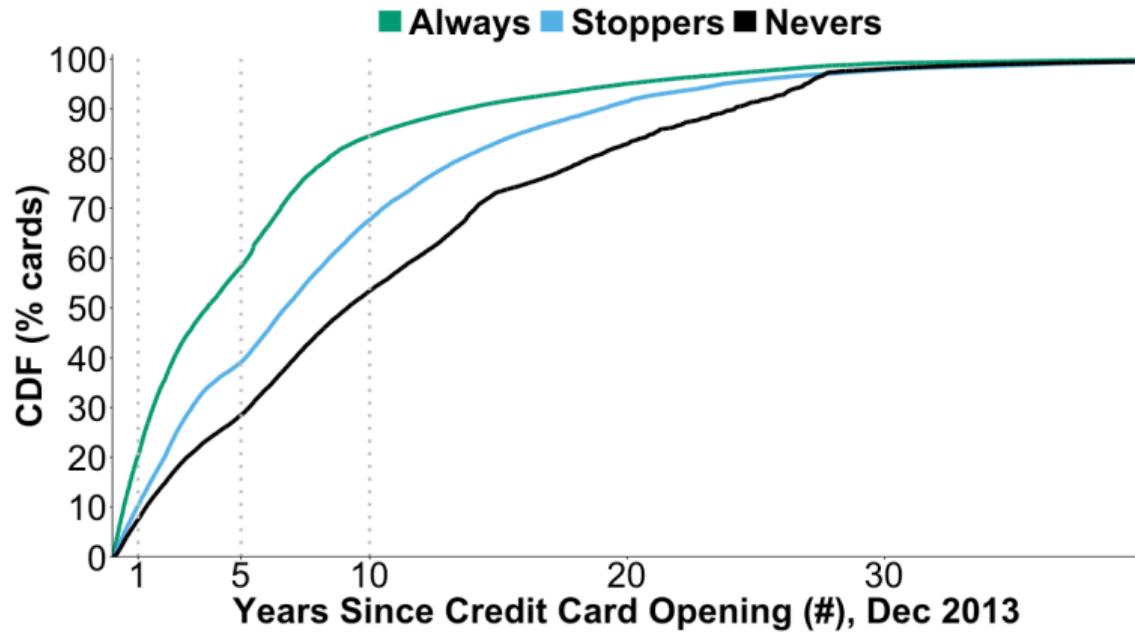


How Is Trended Data Marketed & Used?

- Market response to CARD Act that limited fees (Agarwal et al., 15) & interest (Nelson, 22). Interchange fees increasingly important revenue stream.
- Mainly appears useful for **targeted marketing**:
“Helps Clients...calculate profit by providing an estimate of consumer spend...prioritize marketing investments and target higher spending consumers...optimize enhanced value propositions to the right spending segments.” - Experian.
“A national bank wanted to build more market share and also proactively target consumers who are more likely to be high spenders in the next 12 months. They needed a solution to more accurately predict propensity to spend while creating profitable returns on marketing investments.” - Equifax.
- Some **credit risk** benefit:
“Including trended data materially improved modeling of loan performance.”
- Fannie Mae (consistent with Equifax, Experian, TransUnion, FICO & VantageScore).

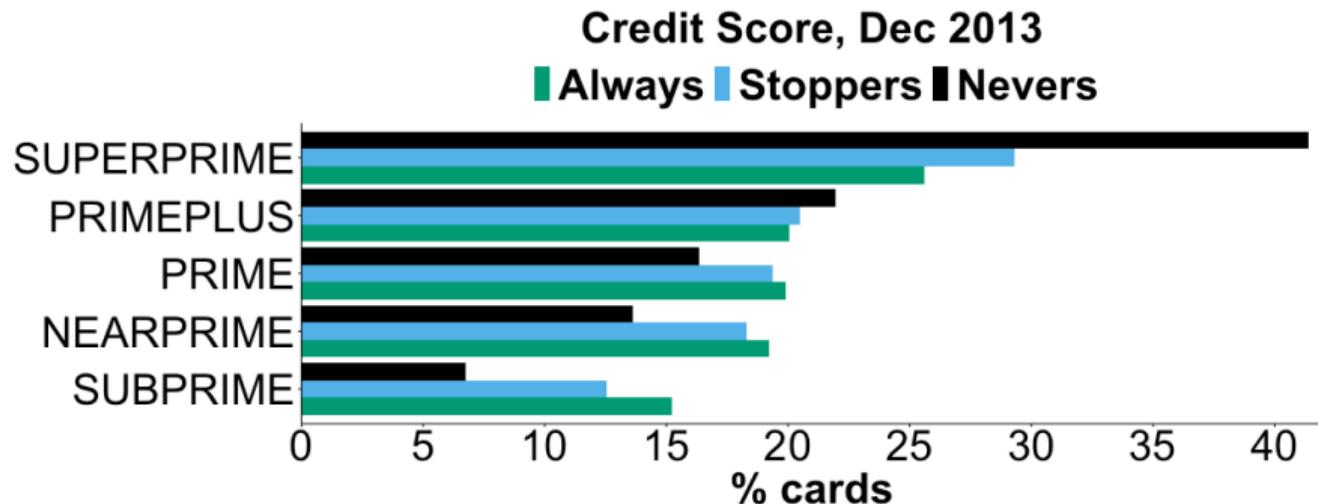
Appendix: Heterogeneity

Adverse Selection of Firm Reporting By Tenure.



Nevers have more long-tenure consumers than Stoppers or Always.

Adverse Selection of Firm Reporting By Credit Score.

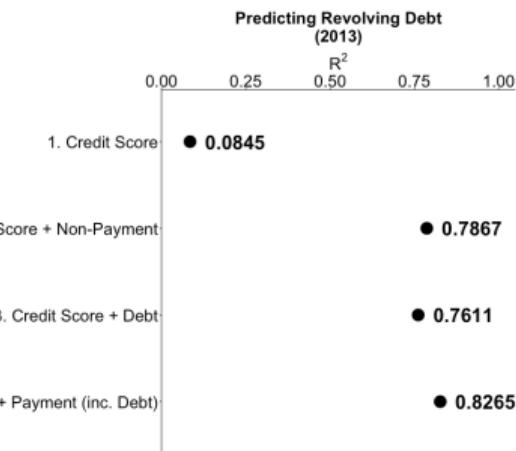


Never have more Superprime than Stoppers or Always.

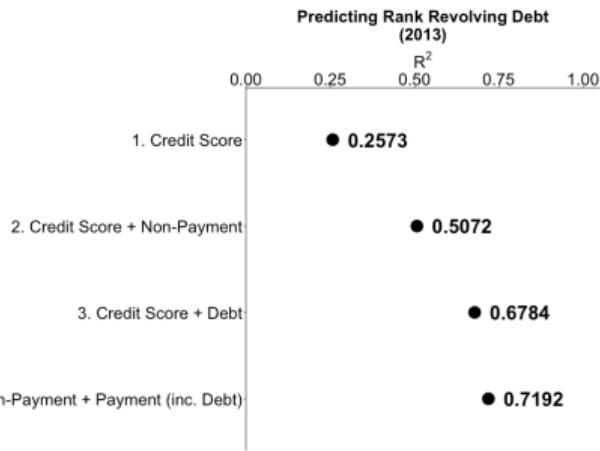
Predicting \$ Revolving Debt (2013) Using OLS on 2012 Data

Prediction models
(2012 data, OLS)

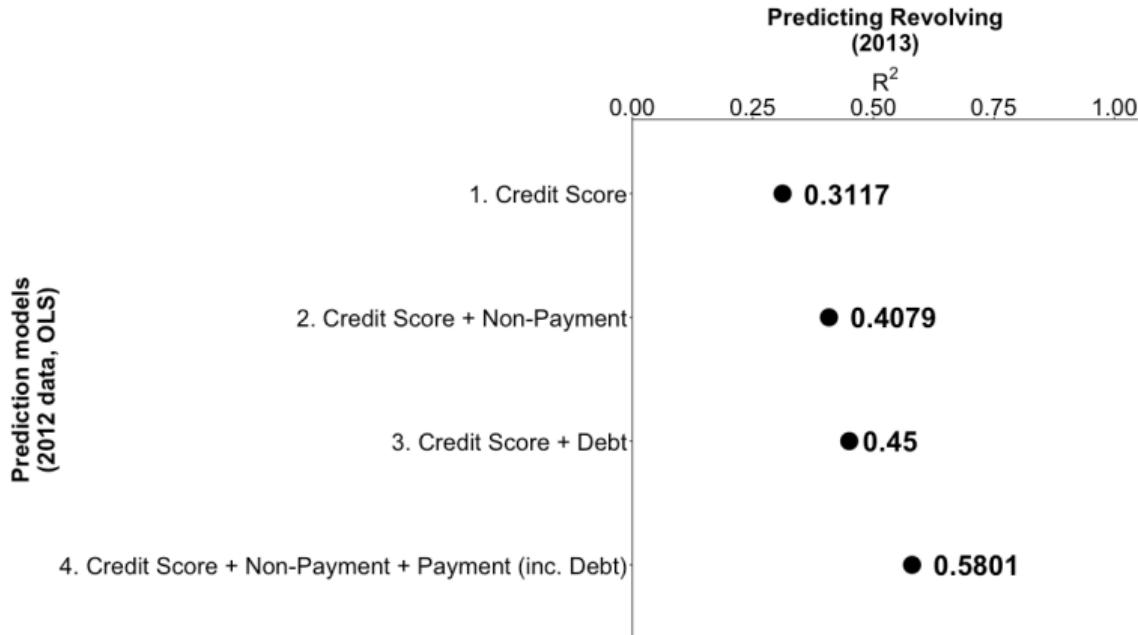
Mean \$



Rank

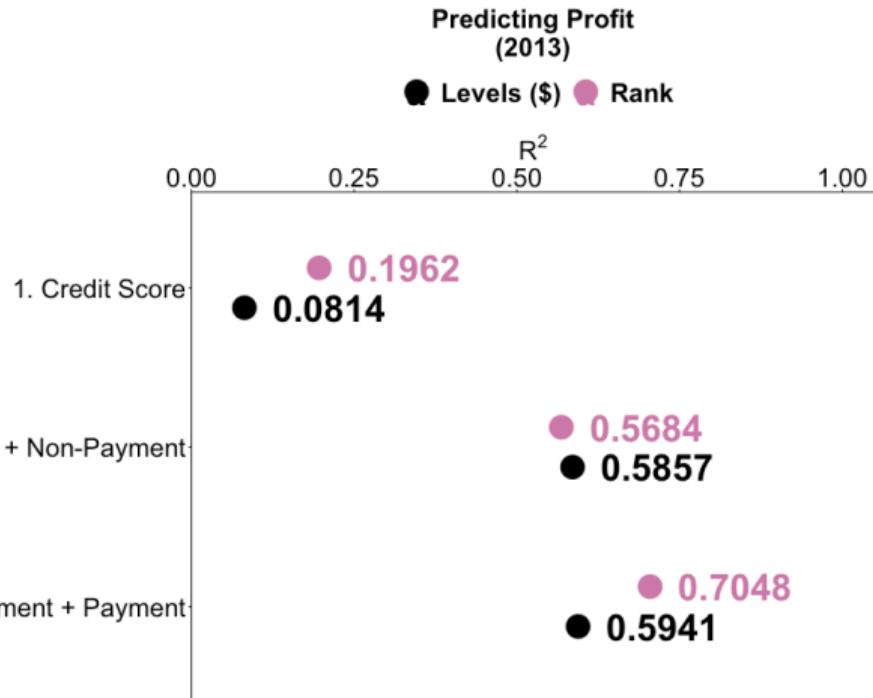


Predicting Majority of Months Revolving Debt (2013) Using OLS on 2012 Data



Predicting Profitability: Profits

Prediction models
(2012 data, OLS)



Appendix: Profits

Sources of Profitability Across Firms

Multiple sources of profitability in credit card market:

$$\text{Profits} = (\text{Interchange Fees} - \text{Rewards}) + (\text{Interest Revenues} - \text{Defaults}) + \text{Other Fees}$$

- Interchange Fees - Rewards \propto Spending.
- Interest Revenues \propto Debt (i.e. Revolving Balances).
- Defaults \propto Credit Score.
- Other Fees (e.g. late fees, foreign exchange fees, annual fees) not based on credit data but private information.
- Lifetime profitability increases with tenure.

Sorting People into Heterogeneous Types Central To Credit Card Business Models

- Phase 1. Predict credit risk (defaulting)
 - Determines price & quantity of credit
- Phase 2. Predict revolvers & high spenders
 - Interest & interchange revenues

Sorting People into Heterogeneous Types Central To Credit Card Business Models

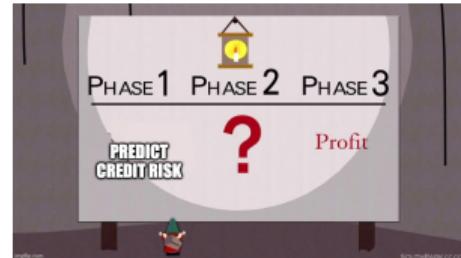
- Phase 1. Predict credit risk (defaulting)
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- Phase 2. Predict revolvers & high spenders
 - Interest & interchange revenues
- Phase 3: Profit

Sorting People into Heterogeneous Types Central To Credit Card Business Models

- Phase 1. Predict credit risk (defaulting)
 - Determines price & quantity of credit
- Phase 2. Predict revolvers & high spenders
 - Interest & interchange revenues
- Phase 3: Profit

Profits Per Credit Card =

- + Interest Income (**Revolvers**)
- + Interchange Income
(Mainly High-Spending **Transactors**)
- + Fees
- Charge Offs (**Revolvers**)
- Rewards (Mainly High-Spending **Transactors**)
- Other Costs



Credit file data used to:

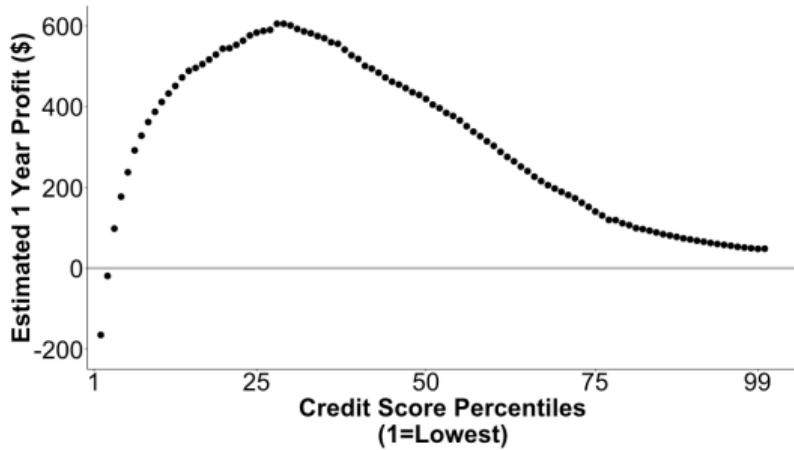
- (i) assess credit risk
- (ii) target marketing to acquire profitable consumers.

“Revolvers”:

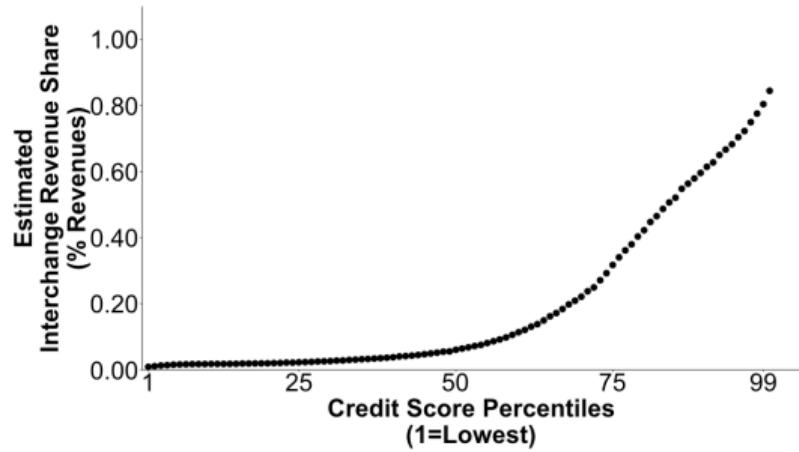
$\text{payment} < \text{statement balance}$
“Transactors” if \geq).

Estimated profits (very much work-in-progress!) by credit score

Estimated 1 Year Profits



Estimated Interchange Revenue Share



$$PROFIT = ((r \times RevolvingDebt) - (d \times DefaultBalance)) + (f \times Spending) + \text{Fees}$$

Assumptions:

- (i) r: Interest rate linear in credit score: 5%-40%.
- (ii) d: Default rate. Assume DefaultBalance has 0% recovery.
- (iii) f: Interchange fees (net of rewards) constant fraction of spending: 0.5%.

Appendix: Stylized Firm's Problem

Stylized framework: Setup

Firm i 's objective is to maximize expected (customer lifetime) profitability ($E_i[\pi|s_i]$).

Firm's choices:

- (a) Investment decision for how many informational signals ('data') about consumer's expected profitability $s_i \in [0, 1]$ to invest in.
- (b) Send marketing ($m_i = 1$) or not ($m_i = 0$) based on expected profitability.

3 time periods:

$t = 0$: Decision to invest in informational signals.

$t = 1$: Decision to send marketing.

$t = 2$: Consumer types realized and profits generated.

Stylized framework: Firm's Problem

$$\max_{m_i \in \{0,1\}} \max_{s_i = [0,1]} m_i \cdot \left(\phi\left(E_i[r(\theta)|s_i], E_i[m_{-i}]\right) - c \right) - f(s_i)$$

$c > 0$ Marketing cost.

$\theta \sim G(\mu, \sigma^2)$ distribution of consumer behavioral types.

$r(\theta)$ Consumer net revenues for consumer type θ .

$\phi(\cdot)$ Expected converted revenues if send marketing.

$E_i[r(\theta)|s_i] - \mu \rightarrow 0, \text{VAR}_i[r(\theta)|s_i] - \sigma^2 \rightarrow 0$ as $s_i \rightarrow 1$. Benefits of investing in signals.

$f(s_i)$ Convex cost of investing in signals.

Stylized framework: Firm's Optimal Decision

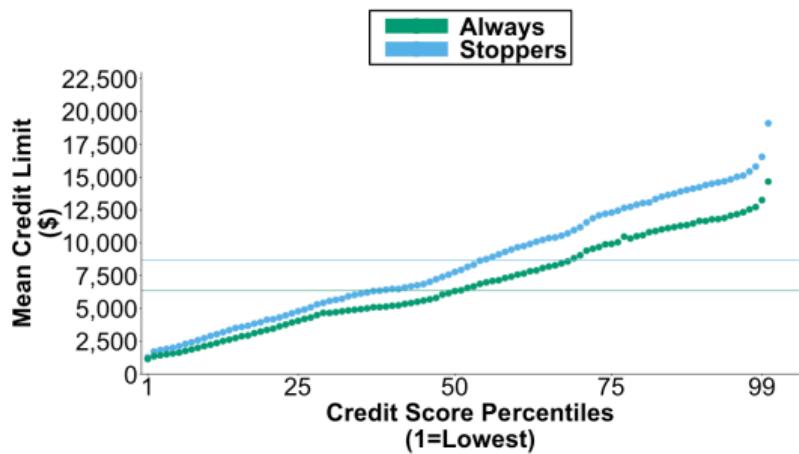
$$\max_{m_i \in \{0,1\}} \max_{s_i = [0,1]} m_i \cdot \left(\phi(E_i[r(\theta)|s_i], E_i[m_{-i}]) - c \right) - f(s_i)$$

- Send marketing: $m^* = 1$ if $\phi(E_i[r(\theta)|s_i], E_i[m_{-i}]) \geq c$
I.e. expected converted profitability exceeds costs
(given information & expected marketing decisions of other firms).
- Optimal information investment: s_i^* where $\frac{\partial \phi(\cdot)}{\partial s_i} = \frac{\partial f(s_i)}{\partial s_i}$
I.e. expected marginal benefit equals marginal costs.

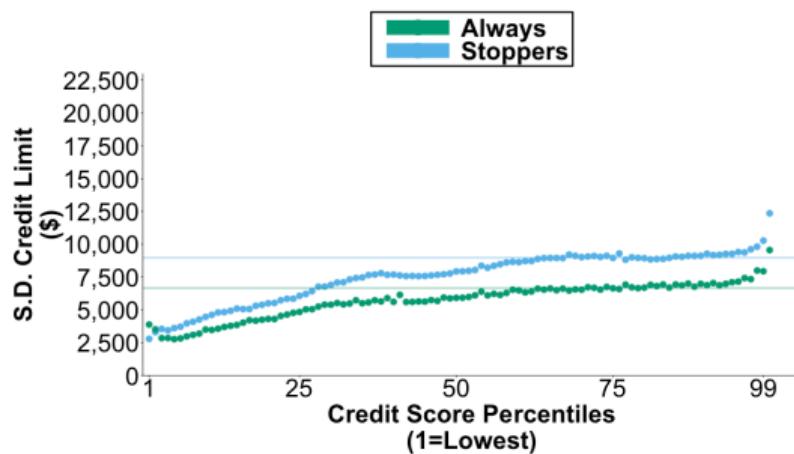
Appendix: Additional Dispersion Charts

Credit Limit

Mean

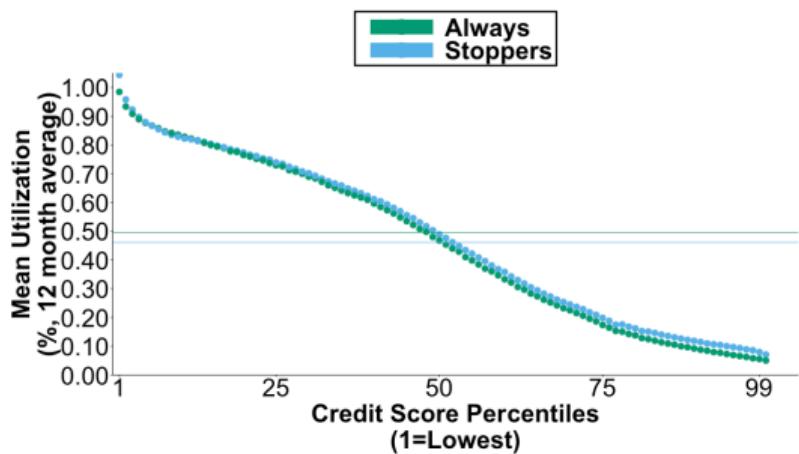


S.D.

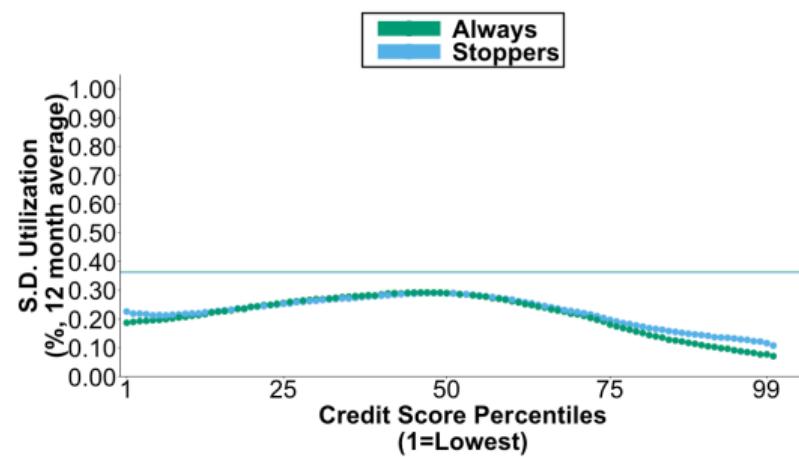


Utilization

Mean

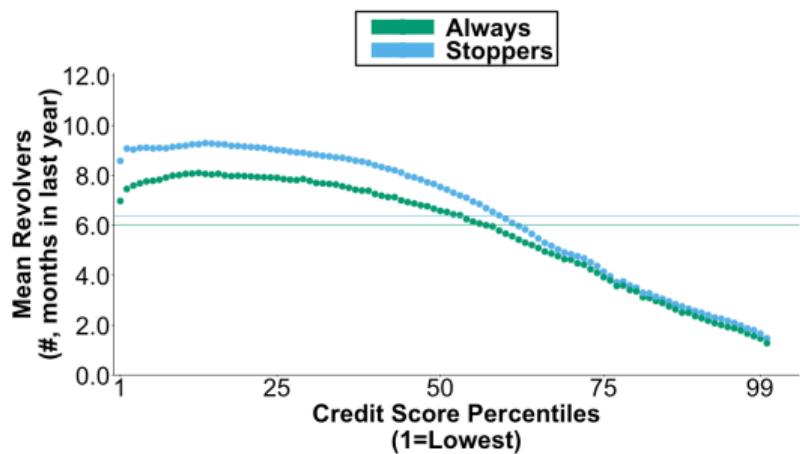


S.D.

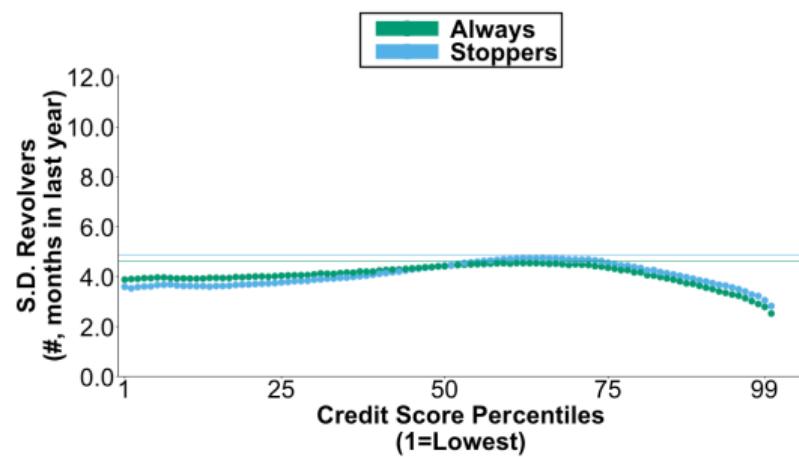


Months Revolving Debt

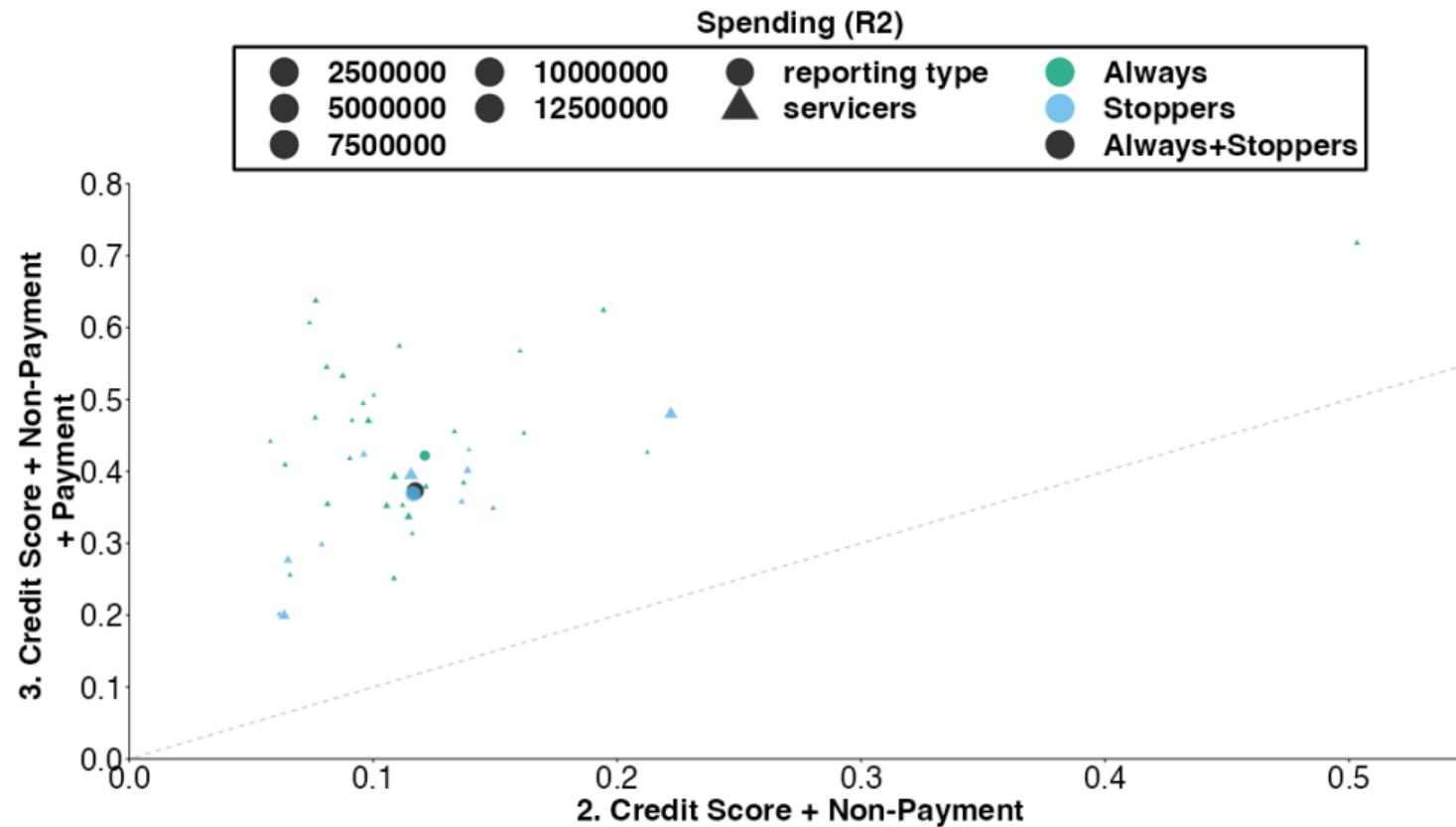
Mean



S.D.



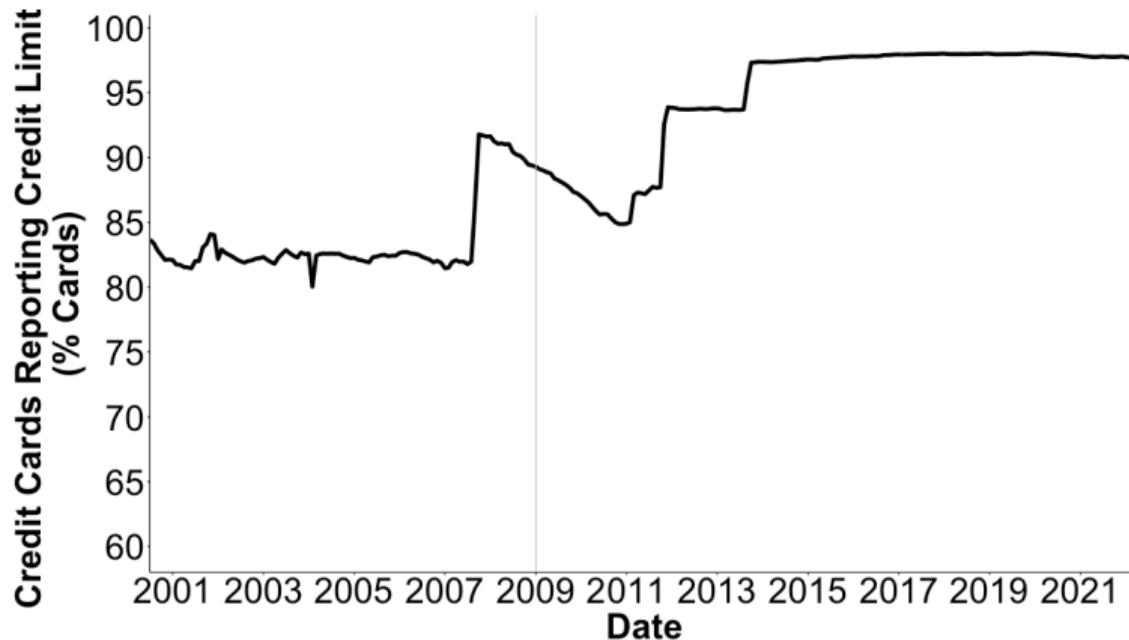
Heterogeneity in Predicting Spending & Value-Add of Payments Data Across Firms



Appendix: Market Design

Exogenous Increases in Credit Card Credit Limit Reporting (2007, 2011, 2013)

- Driven by FTC



Learn what happens when firms are forced to share.

Effects Of Unraveling On Market

- Trended Data Appears Efficient Innovation
(e.g. Fannie Mae (2016), VantageScore 4.0 (2017), & FICO 10 (2020))
- Non-Reporting & Unraveling Inefficient
(Adverse Selection of Servicers)

Market design solutions?

A. Ban Use Of Credit Files For Marketing

- No unraveling in reporting in UK or Canada where this system occurs.
- Unclear welfare impact (less marketing vs. improved credit risk)

B. Reciprocity: Only able to use payments data if share payments data (UK system).

C. Regulatory Requirement

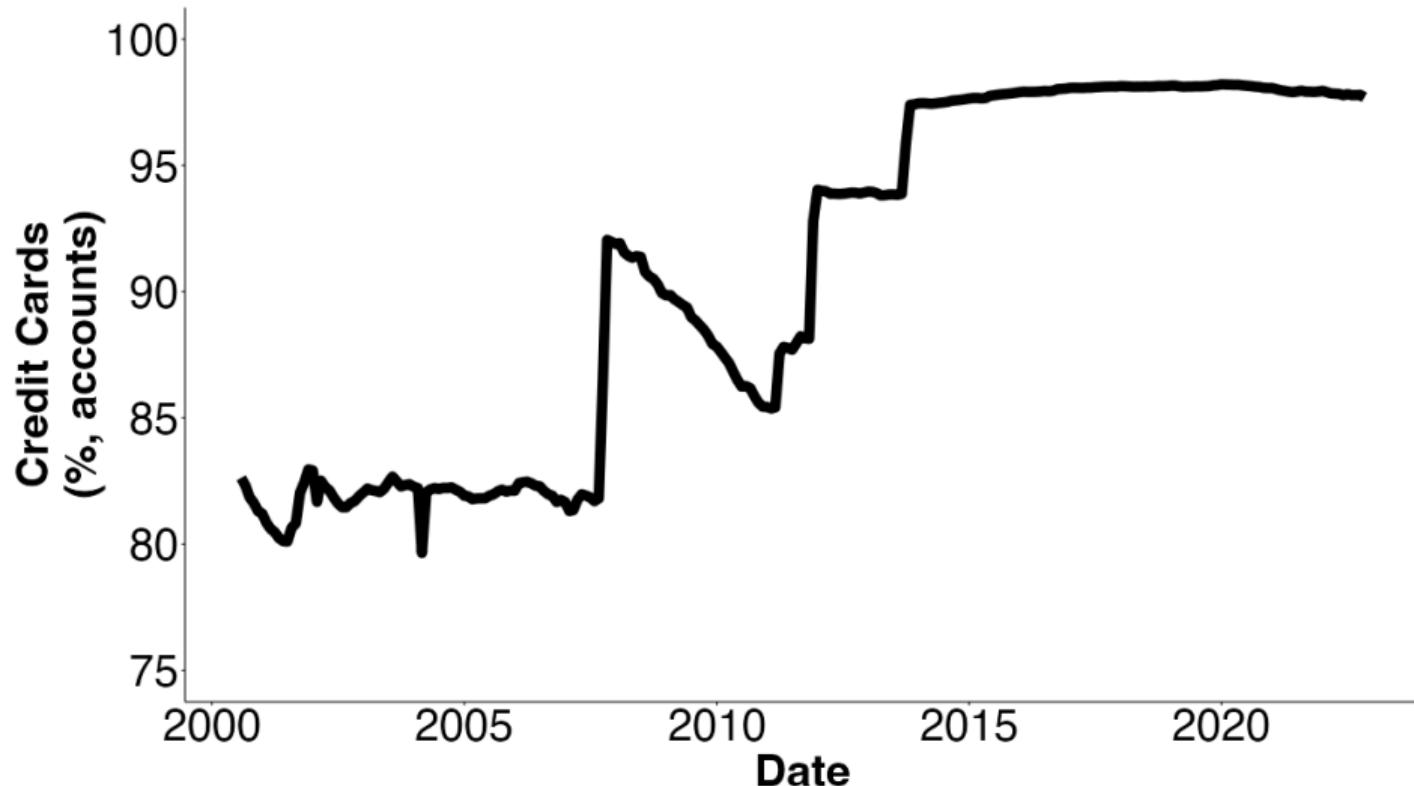
- Regulatory: CFPB / Fed / Treasury “require” reporting as done with credit limits.
(via ‘soft’ supervisory power or ‘hard’ law)

Understanding Credit Reporting

What would be the effects of a counterfactual regulation requiring credit card lenders to report data?

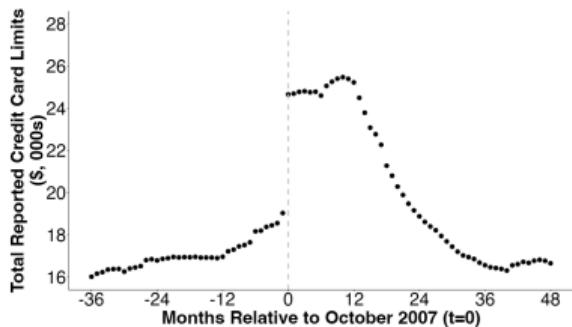
1. Market effects of reporting (efficiency, strategic reactions, competition).
2. Effects on consumer outcomes (credit score, credit access).
3. A new source of exogenous variation other researchers can use more broadly.
4. Clean empirical application of seminal theoretical finance literatures on (i) relationship lending (inside vs. outside) and (ii) credit reporting.

Credit Card Credit Limit Reporting

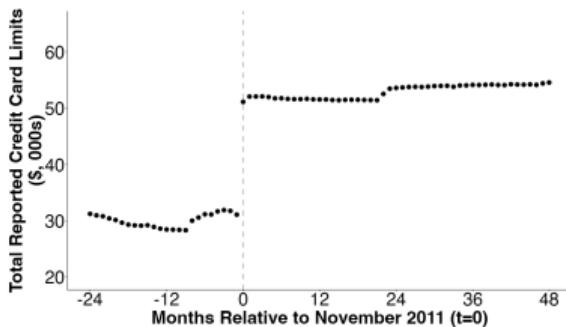


3 Events of Lenders Starting Reporting of Credit Card Credit Limits

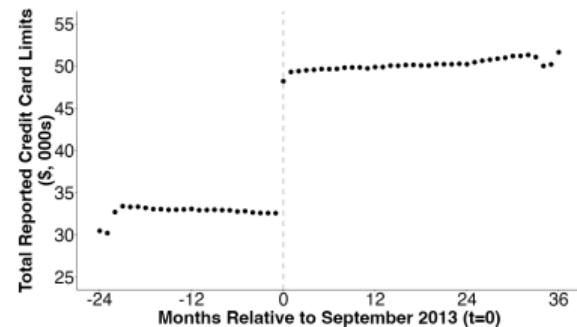
2007
14.00 mn



2011
12.85 mn consumers



2013
5.70 mn



FTC action (announced 2009, in rules 2011) required firms to report credit limits
(if firms decide to voluntarily report data to bureaus).

Fair and Accurate Credit Transactions Act (FACTA 2003, Revised 2011).

What Does Credit Limit Reveal?

Utilization Behavior: Key input to credit scores.

- If credit limit not reported, highest historical balance is utilization denominator.

Lenders can use to inform consumer's **expected profitability** for poaching. Learn about:

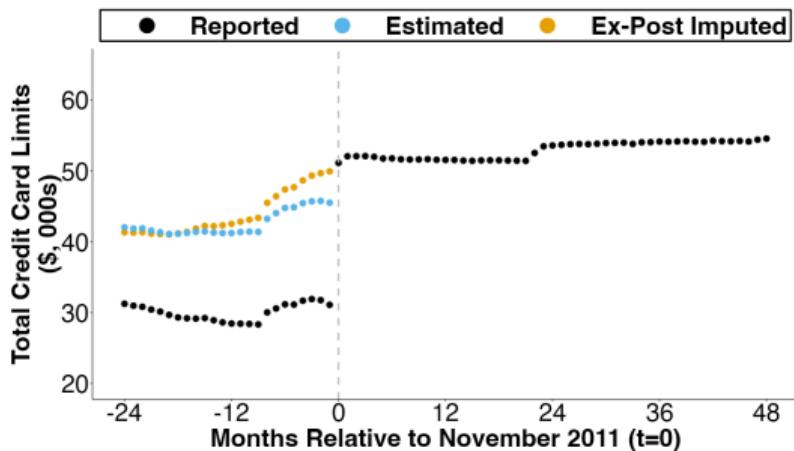
1. Consumers' behavioral type.
2. Credit limit their competitors (who have private information) are willing to extend.

N.b. as shown previously, credit utilization reveals very little about spending and not much about revolving behavior.

Credit Card Credit Limits

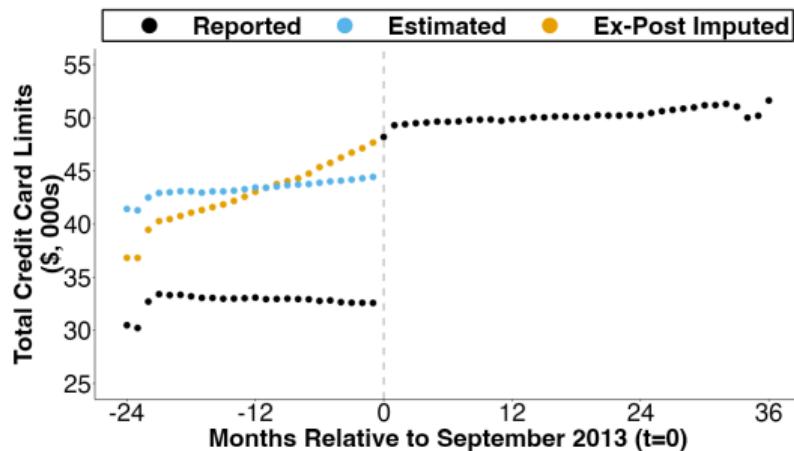
2011

12.85 mn consumers



2013

5.70 mn

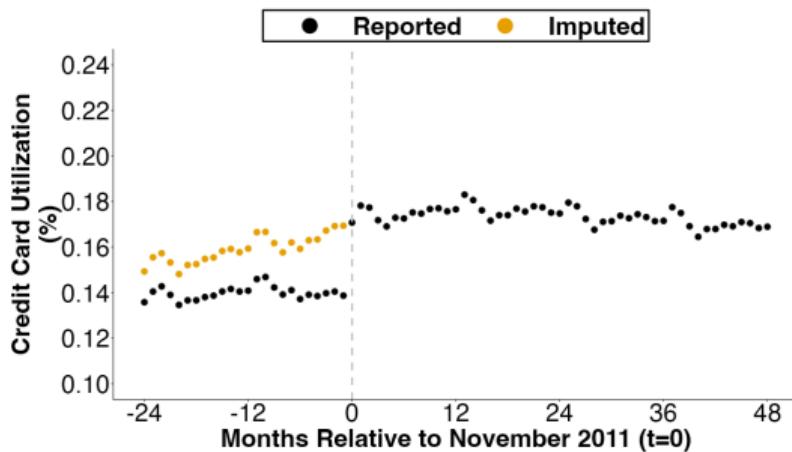


- **Reported:** Credit limit amount reported.
- **Observed:** Highest statement balance amount previously reported on tradeline.
- **Imputed:** Take reported credit limit at t=0 and impute for pre-periods where tradeline open.

Credit Card Utilization

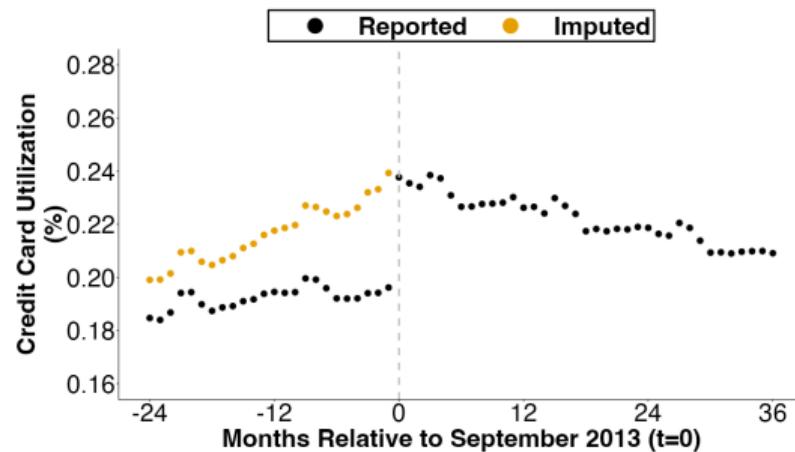
2011

12.85 mn consumers



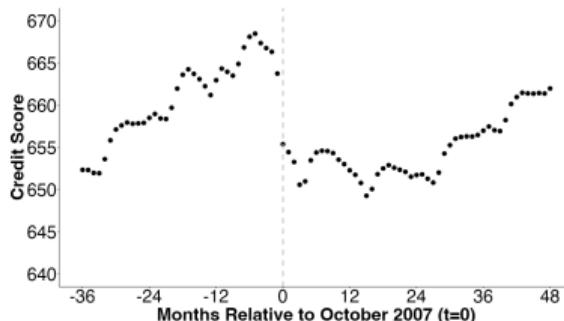
2013

5.70 mn

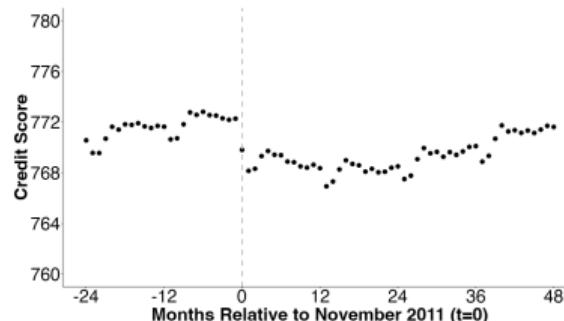


Credit Score

2007
14.00 mn consumers



2011
12.85 mn consumers



2013
5.70 mn

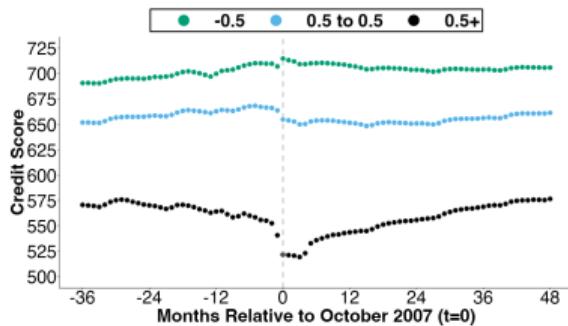


- Lower score as more utilized than observed using highest historical statement balance.
- Must mean highest historical statement balance > current credit limit.
- i.e. Limits on these cards declined (on average). Makes sense given crisis timing.

Credit Score

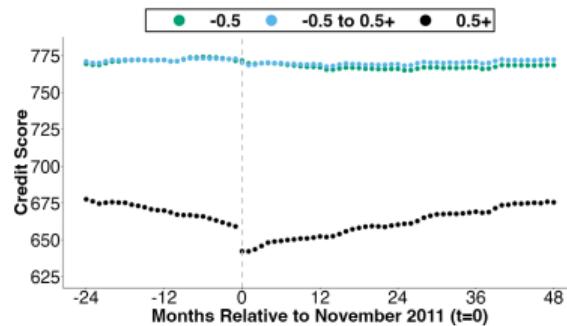
2007

14.00 mn consumers



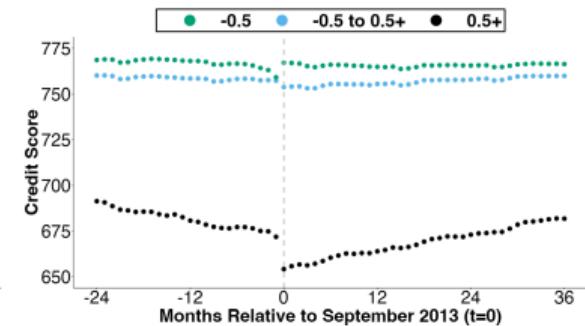
2011

12.85 mn consumers



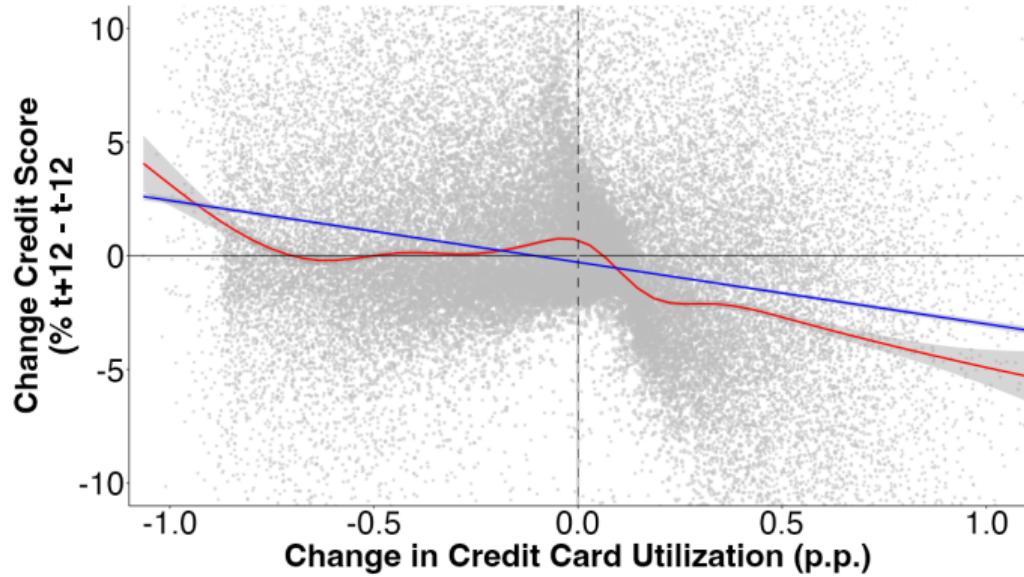
2013

5.70 mn consumers



HTE by change in utilization: $\frac{Balance_{t-1}}{CreditLimit_t} - \frac{Balance_{t-1}}{HighBalance_{t-1}}$

Δ Utilization x Credit Score



HTE by change in utilization: $\frac{Balance_{t-1}}{CreditLimit_t} - \frac{Balance_{t-1}}{HighBalance_{t-1}}$

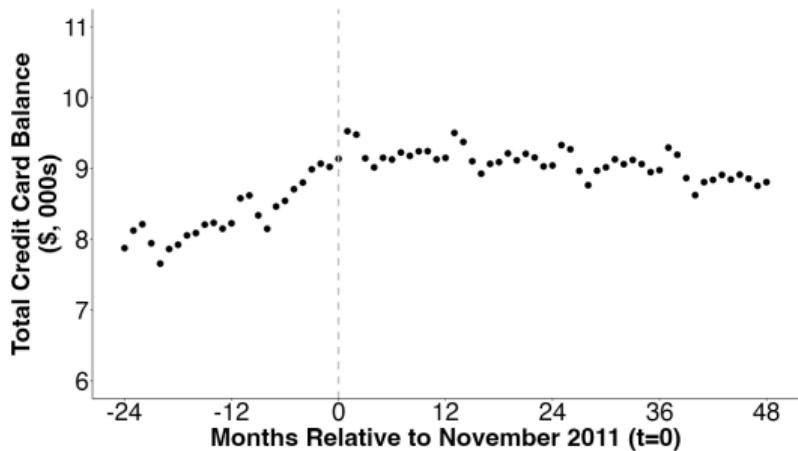
i.e. how much *new* information

- will do other HTE cuts (e.g. \$ limits, portfolio utilization, credit score).

Credit Card Statement Balance

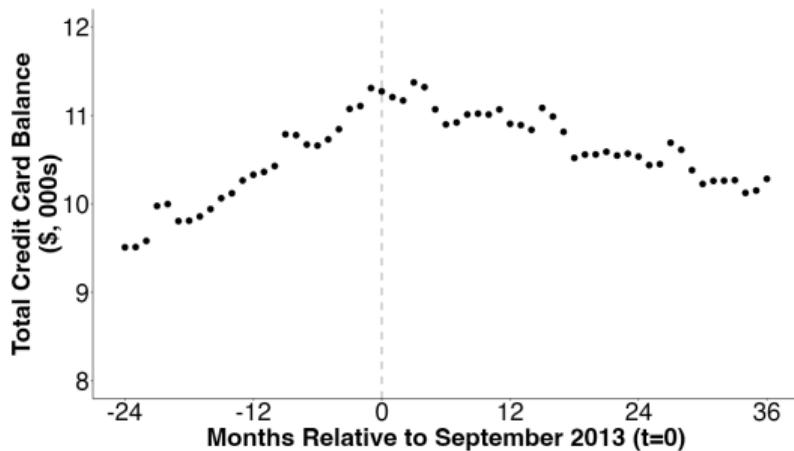
2011

12.85 mn consumers



2013

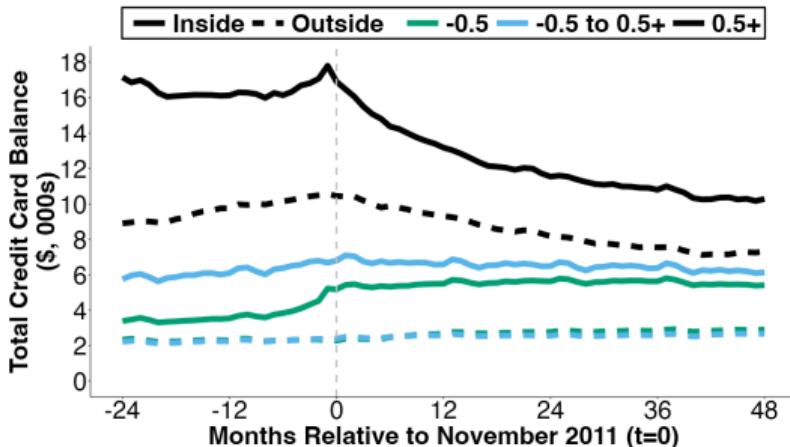
5.70 mn



Credit Card Statement Balance

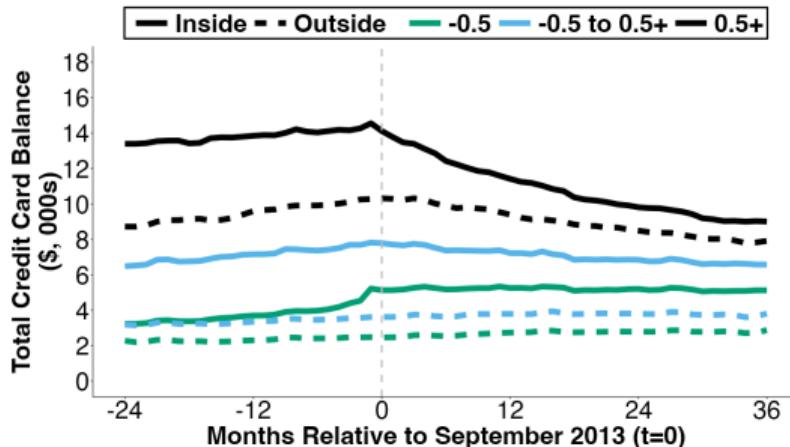
2011

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2013

5.70 mn

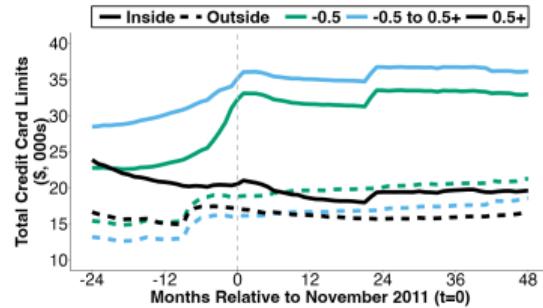


- HTE by change in utilization: $\frac{Balance_{t-1}}{CreditLimit_t} - \frac{Balance_{t-1}}{HighBalance_{t-1}}$
- **Inside:** Lenders who started reporting credit limits. **Outside:** All other lenders.

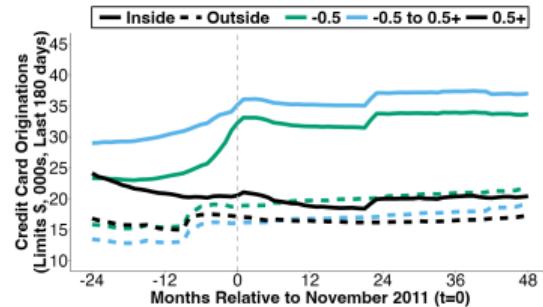
Credit Card Credit Limits

2011

Credit card limits (portfolio).

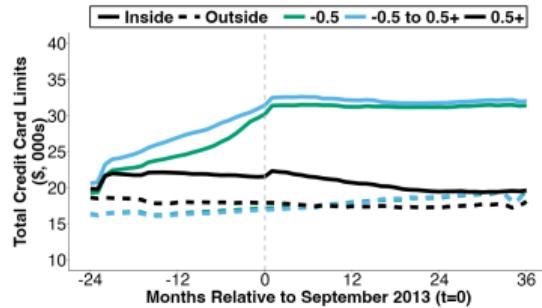


Credit card limits (originations).

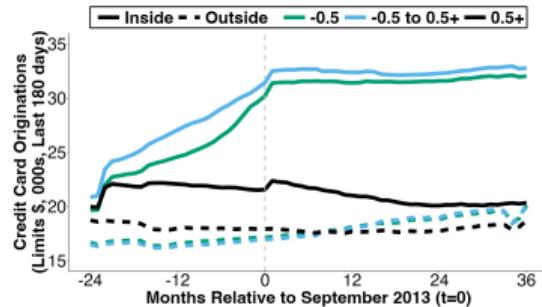


2013

Credit card limits (portfolio).



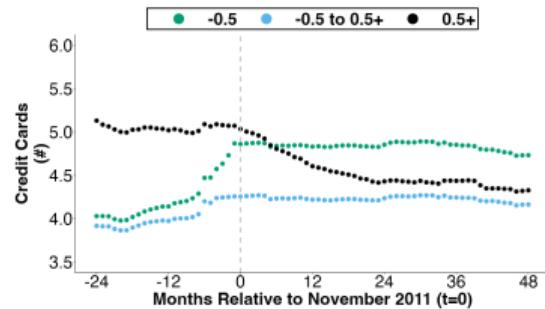
Credit card limits (originations).



Number Credit Cards

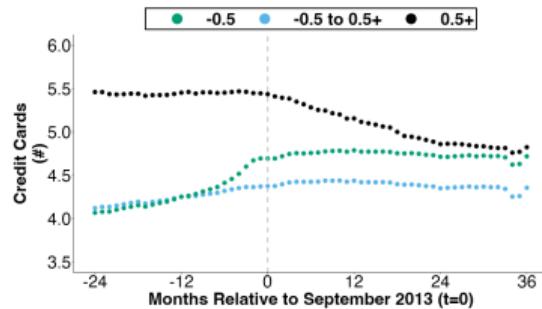
2011

Number credit cards (portfolio).

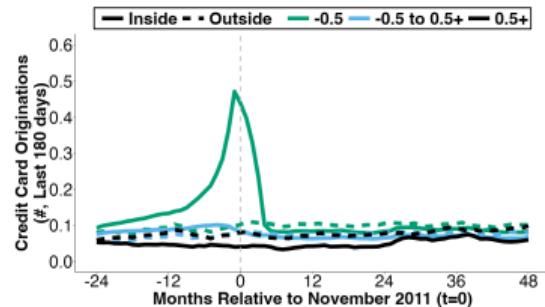


2013

Number credit cards (portfolio).



Number credit cards (originations).



Number credit cards (originations).

