A Share Too Far: How Data Innovation Unraveled U.S. Credit Card Information Sharing

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Calculated (or derived) based on credit data provided by TransUnion, a global information solutions company, through a relationship with the Kilts Center for Marketing at the University of Chicago Booth School of Business. TransUnion (the data provider) has the right to review the research before dissemination to ensure it accurately describes TransUnion data, does not disclose confidential information, and does not contain material it deems to be misleading or false regarding TransUnion, TransUnion's partners, affiliates or customer base, or the consumer lending industry.

Context

- On finance & economics job market in 2023-24.
- Aiming for for 1st full draft for start of Spring term.
- Want big picture feedback on today's research:
  - How to appeal to finance / general audience?
  - Where gaps to prioritize efforts?

One Slide Summary

US credit markets regarded as the most developed in the world.

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Research Questions:

How & why did the US credit cards market unravel? Why credit cards and not in other US credit markets?

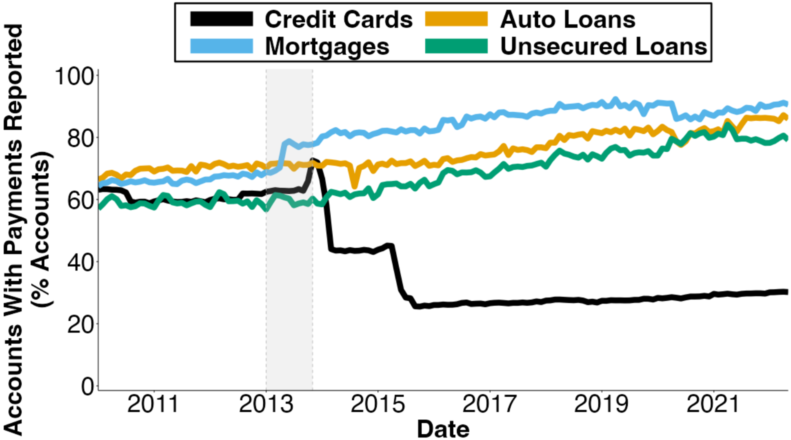
Data:

University of Chicago Booth's TransUnion Consumer Credit Panel (BTCCP).

Key Interim Findings:

- Unraveling driven by innovation (Trended Data) enhancing profitability prediction.
- Unraveling due to multiple sources of information asymmetry beyond credit risk.
- Credit card market – and especially subset of lenders – most affected.
- Lenders most affected stopped reporting data input (payments data) innovation relied on to foreclose on competitors.

Unraveling in Credit Card Reporting of payments Data to US Credit Bureau



What is 'Payments Data'?

e.g. pay $750 against $1,000 credit card statement balance. 'Payment Data' is $750.

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
  - Credit Cards (e.g. Agarwal et al.,15; Nelson, 21)
  - Credit Information (e.g. Foley et al., 21; Blattner, Hartwig & Nelson, 22)

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

cfpb 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

Credit Bureaus Created Innovation in 2013: “Trended Data”

CDIA
CONSUMER DATA INDUSTRY ASSOCIATION

ABOUT RESOURCES EDUCATION SERVICES NEWS, EVENTS, AND BLOGS

July 2, 2020

What is Trended Data and Why Should I Care?

News

TransUnion

PERSONAL BUSINESS PUBLIC SECTOR

Solutions and Products Industries Insights and Events

How trended credit data and alternative data are like a scrapbook

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

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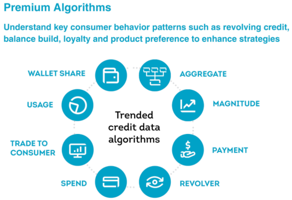
- For **instalment loan** products trends reveal little about consumer profitability beyond credit risk as consumers following a fixed schedule.

- Trends reveal **credit cards** behaviors driving profitability beyond default.

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



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

Predicting Profitability

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 rate or interchange revenue

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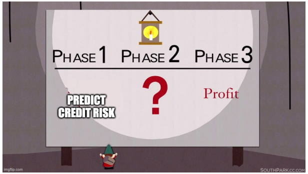

Profits Per Credit Card =

\+ 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":
payment $<$ *statement balance*
(**"Transactors"** if $\geq$).

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Models:

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2. Credit Score + Non-Payment (e.g. credit limit, statement balances, utilization, default)
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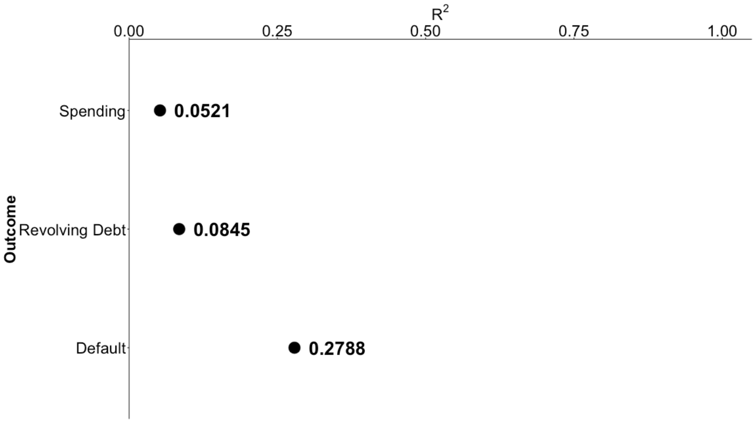
Comparing Model 2 to Model 3 shows informational value of
Trended Data harnessing payments data (to target profitable consumers).

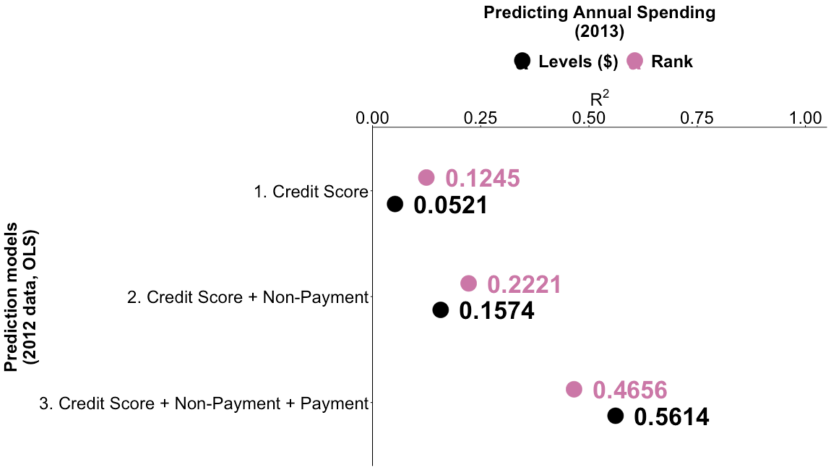
Credit Scores Alone Poor Predictor of Spending & Revolving Debt



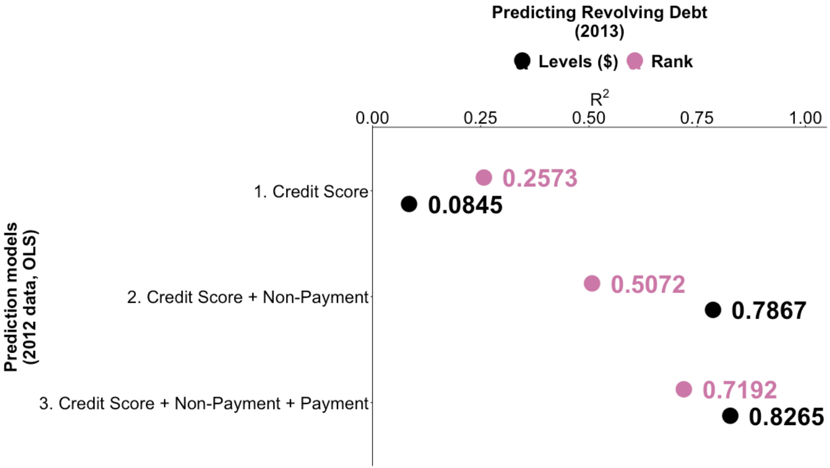
$$Spending_t = balance_t - balance_{t-1} + payment_t$$ (Ganong & Noel, 20 AER)

$$Revolving\ Debt_t = balance_{t-1} - payment_{t-1}$$

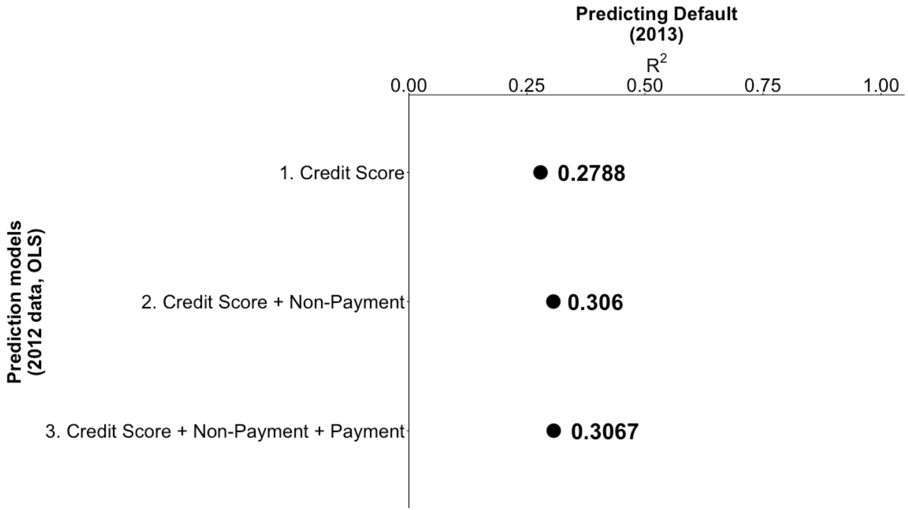
Predicting Profitability: Spending



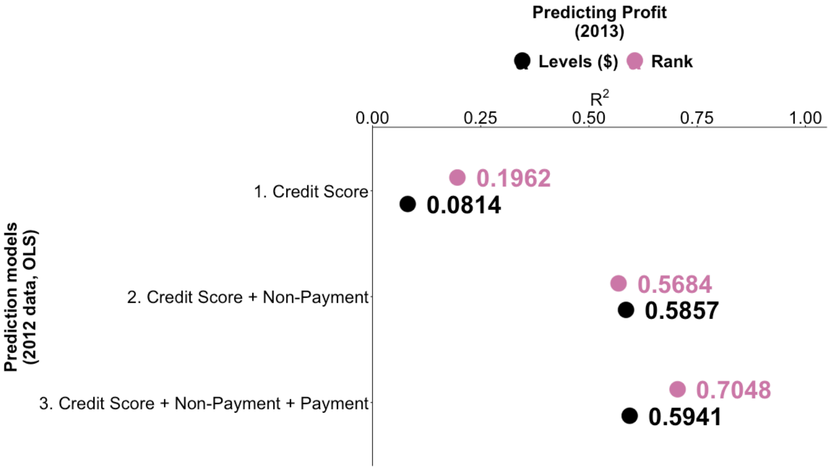
Predicting Profitability: Revolving Debt



Predicting Profitability: Default

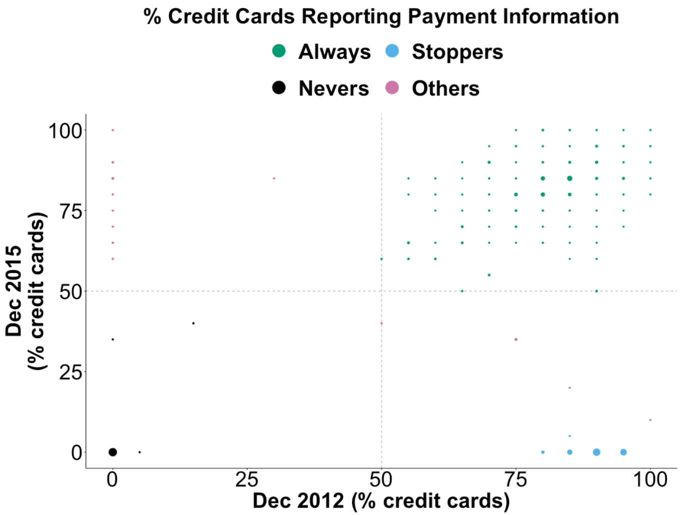


Predicting Profitability: Profits



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.

Nevers: 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.

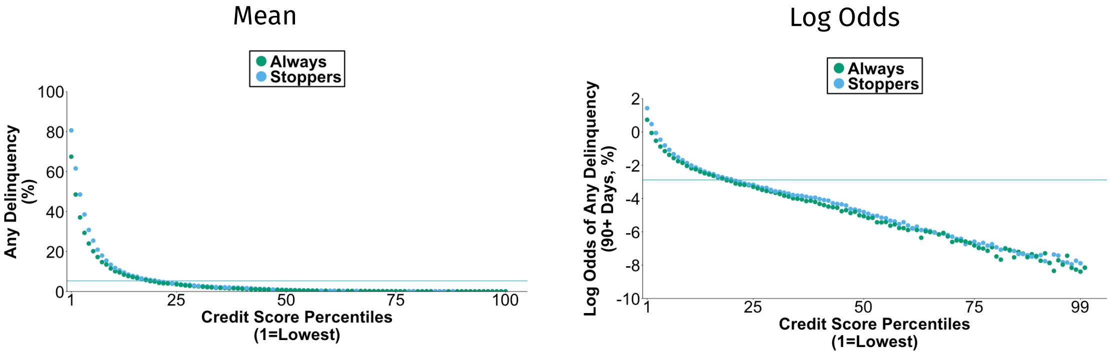
Reporting Repayments Data is Monotonic in Tenure, Credit Limit & Statement Balance (All Residual of Credit Score)

	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.

Credit Card Profits

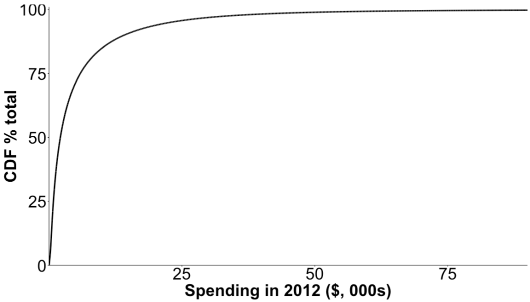
Always & Stoppers Have Similar Default Rates Conditional on Credit Score.



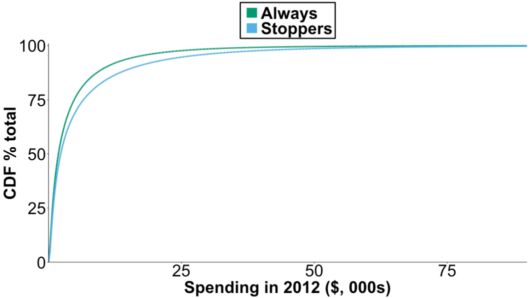
Credit risk doesn't appear to be main reason for differential reporting.

Large Variation in Spending.

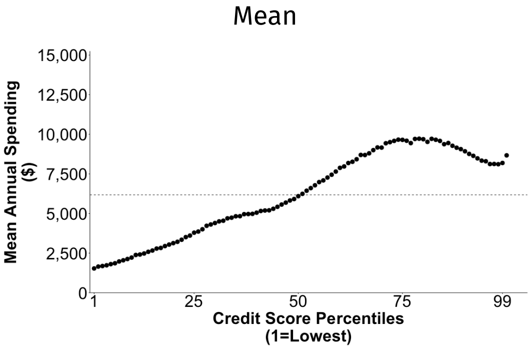
Aggregated Across Always & Stoppers

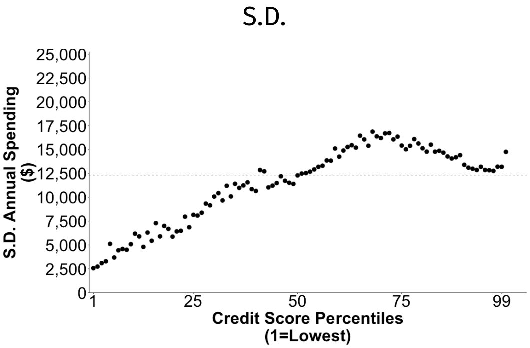


Disaggregated Always vs. Stoppers

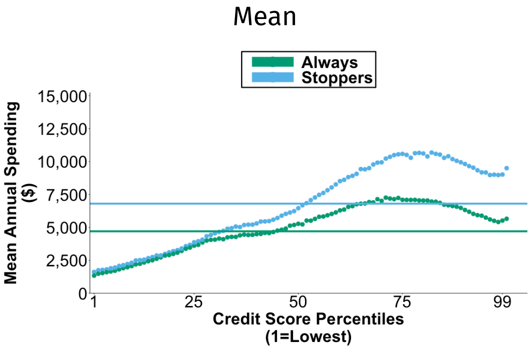


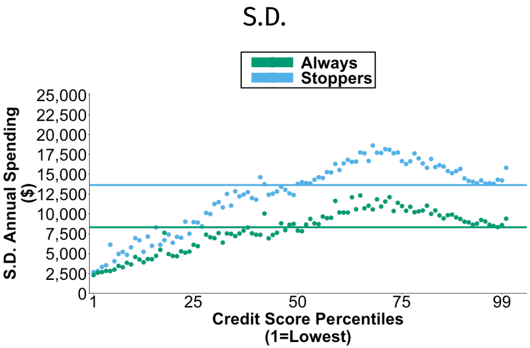
Large Variation in Spending Conditional on Credit Score.





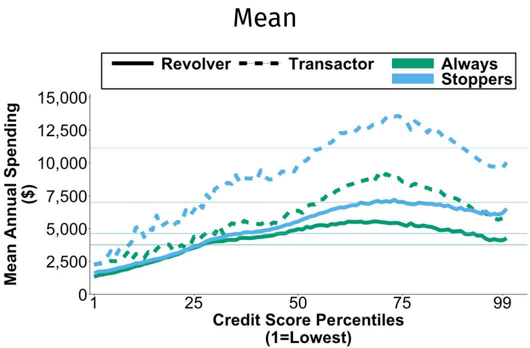
Adverse Selection - Stoppers spend more than Always

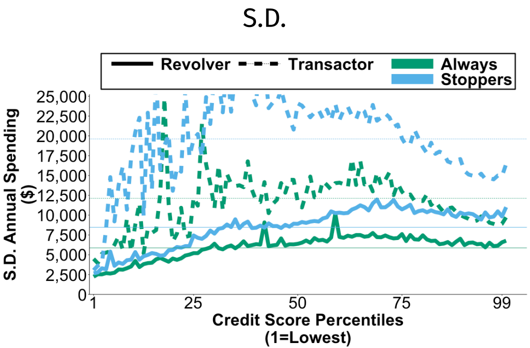




Stoppers higher mean and variance than Always.

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

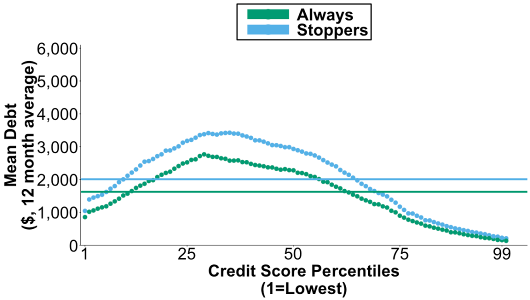




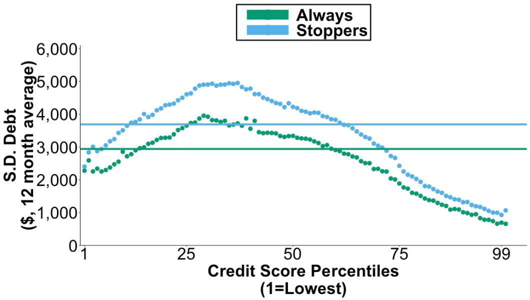
Stoppers higher mean and variance than Always.

Adverse Selection - Stoppers revolve more debt than Always

Mean



S.D.



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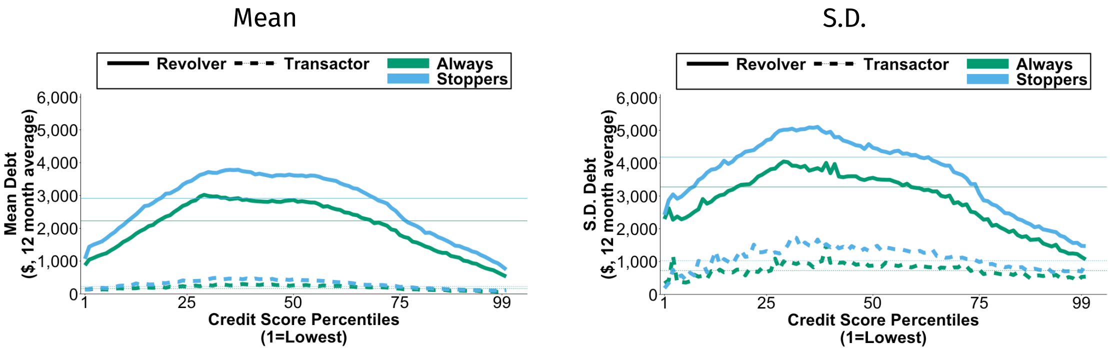

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Predicting Stoppers Credit Card Behaviors By Training Model Using Always Data Performs Poorly

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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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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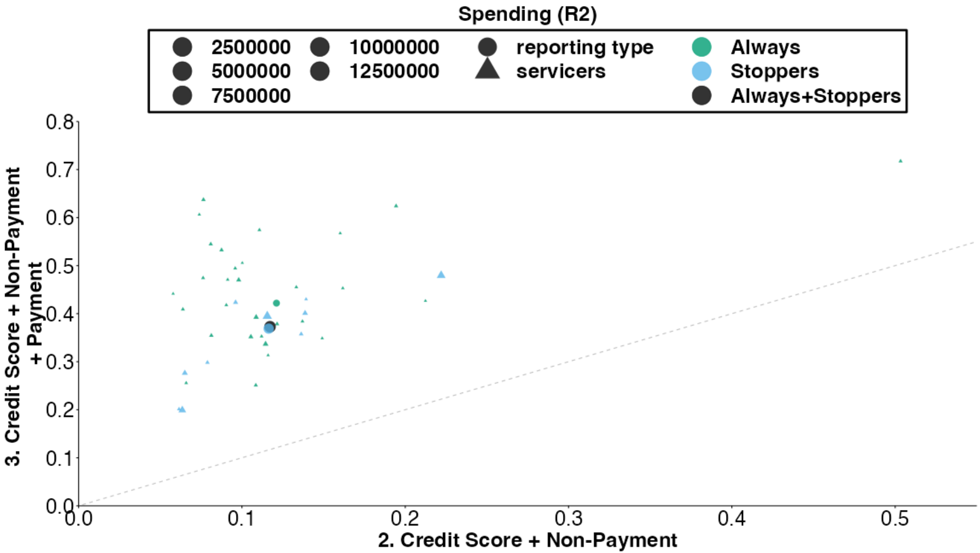
- **Predicting 2013 Spending:**
  $R^2 = 0.175$ out-of-sample for Stoppers
  (vs. 0.458 in-sample for Always).
- **Predicting 2013 Revolving Debt:**
  $R^2 = 0.479$ for Stoppers
  (vs. 0.724 in-sample for Always).

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



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.

Counterfactual Reporting (if Time!)

Conclusions

Lots of Work-in-Progress

- Calculating interest rates to estimate profits across credit products (autos, credit cards, mortgages).
- Price theory model of unraveling
- CreditVision trended data analysis.
  (Thanks to Stigler Center for funding!)
- Effects of reporting information on consumers
  (separate paper).

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 instalment-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).

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

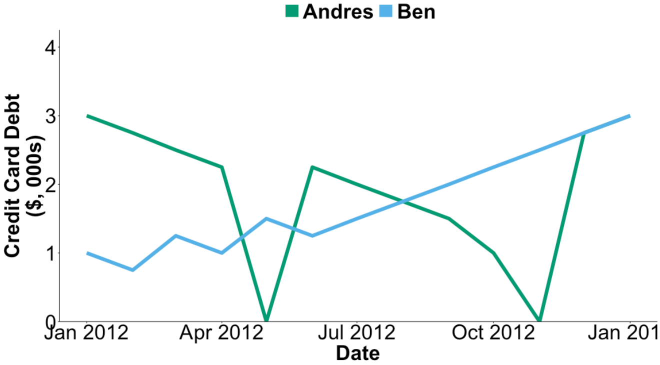
- **Firm Differentiation:** Firms more different (e.g. more loyal customers, more focused on a profitable subsegment), less likely to share.
  - Testable in data comparing consumer bases (e.g. card tenures).
- **Multi-Homing:** Firms where consumers hold other cards, more likely to share.
  - Testable 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.

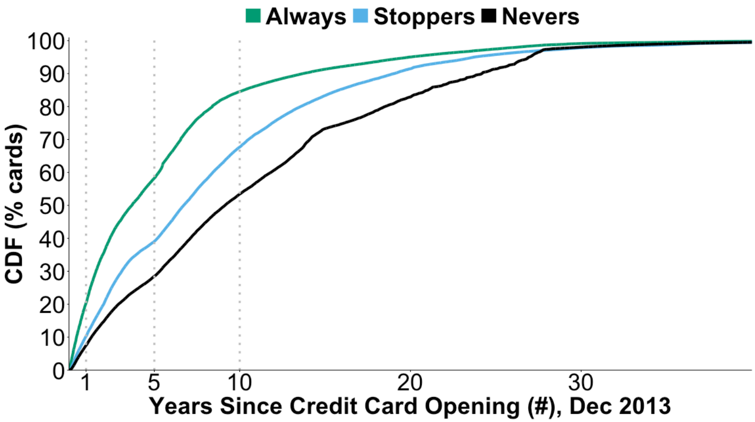


How Is Trended Data Marketed & Used?

- 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).

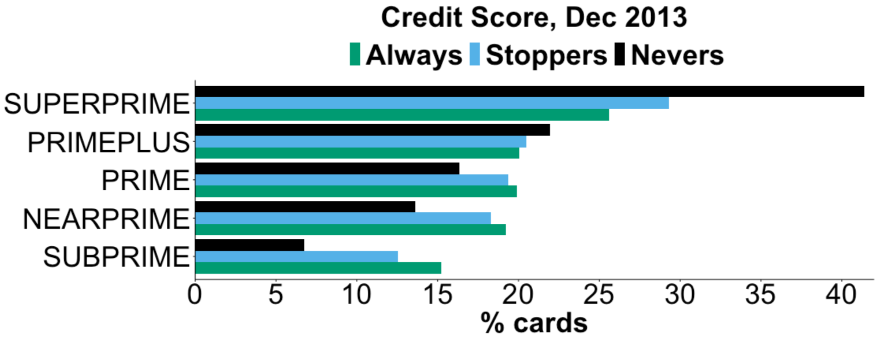
Appendix: Heterogeneity

Adverse Selection of Firm Reporting By Tenure.



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

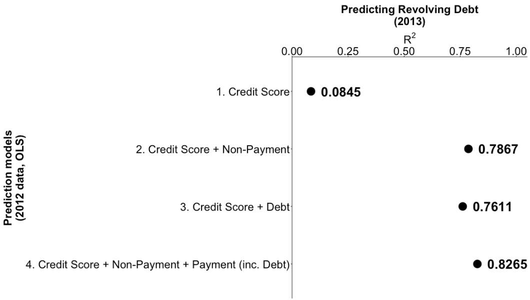
Adverse Selection of Firm Reporting By Credit Score.



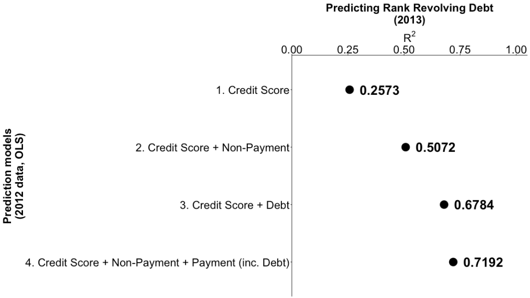
Nevers have more Superprime than Stoppers or Always.

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

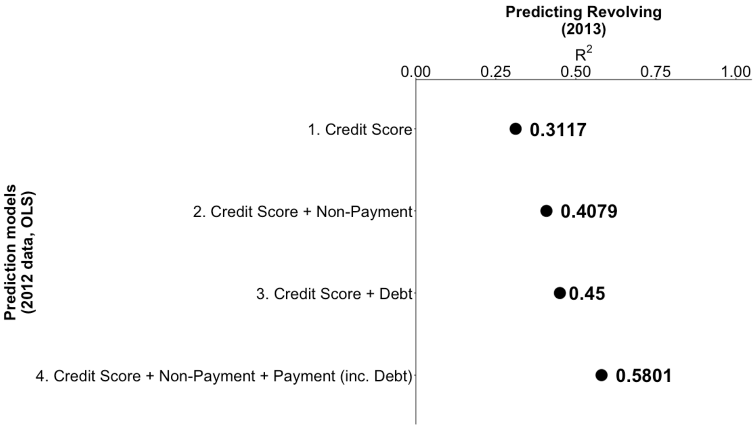
Mean $



Rank



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



Appendix: Profits

Sources of Profitability Across Firms

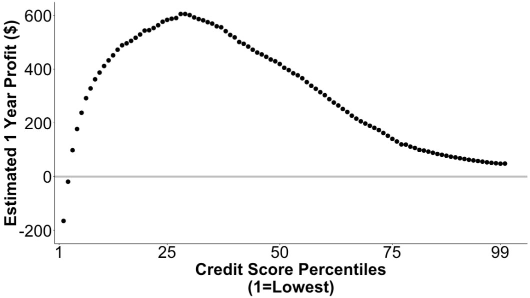
Multiple sources of profitability in credit card market:

Profits = (Interchange Fees - Rewards) + (Interest Revenues - Defaults) + Other Fees

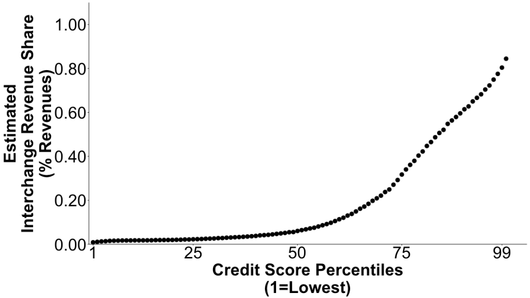
- Interchange Fees - Rewards $\propto$ Spending.
- Interest Revenues $\propto$ Debt (i.e. Revolving Balances).
- Defaults $\propto$ Credit Score.
- Other Fees (e.g. late fees, foreign exchange fees, annual fees) not based on credit data but private information.
- Lifetime profitability increases with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

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

Estimated 1 Year Profits



Estimated Interchange Revenue Share



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

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

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

$c > 0$ **Marketing cost**.

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

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

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

$E_i[r(\theta)|s_i] - \mu \to 0$, $VAR_i[r(\theta)|s_i] - \sigma^2 \to 0$ as $s_i \to 1$. **Benefits of investing in signals**.

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

Stylized framework: Firm's Optimal Decision

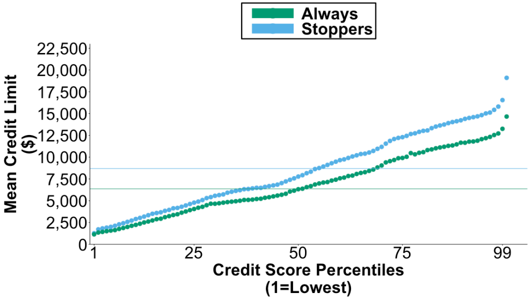
$$\max_{m_i \in \{0,1\}} \max_{s_i = [0,1)} \quad m_i \cdot \left(\phi\Big(E_i[r(\theta)|s_i], E_i[m_{-i}] \Big) - c \right) - f(s_i)$$

- 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 $\frac{\partial \phi(.)}{\partial s_i} = \frac{\partial f(s_i)}{\partial s_i}$
  I.e. expected marginal benefit equals marginal costs.

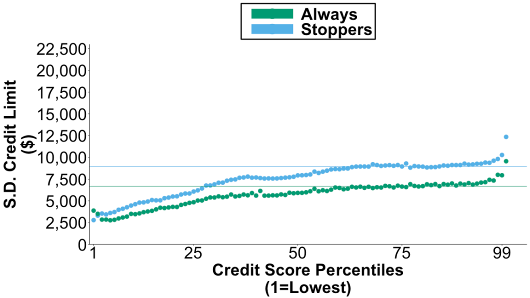
Appendix: Additional Dispersion Charts

Credit Limit

Mean

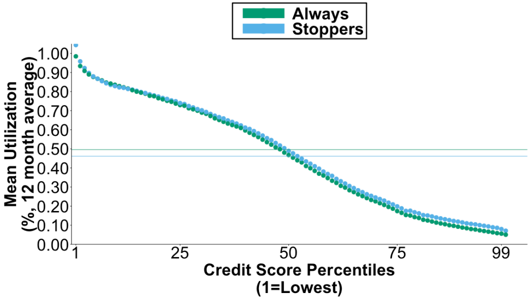


S.D.

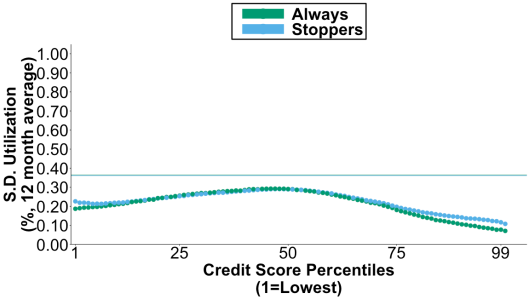


Utilization

Mean

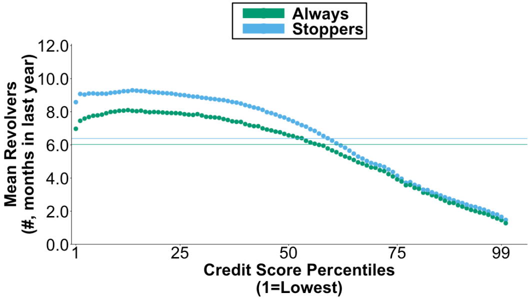


S.D.

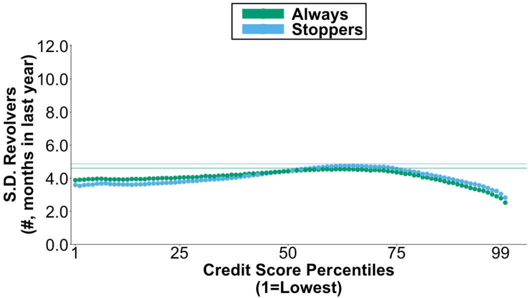


Months Revolving Debt

Mean

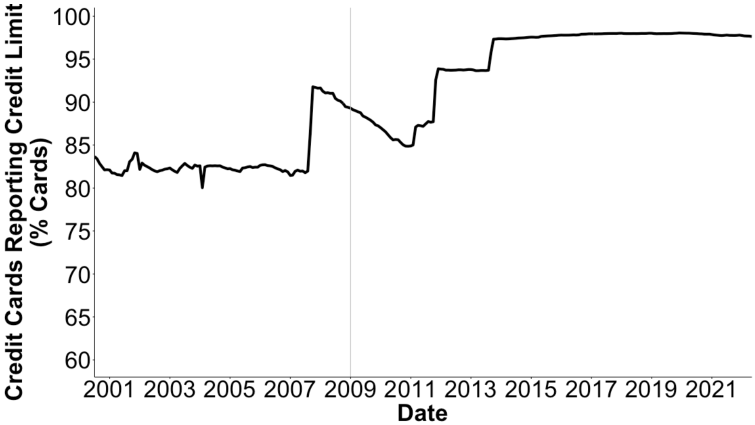


S.D.



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.

C. Regulatory Requirement

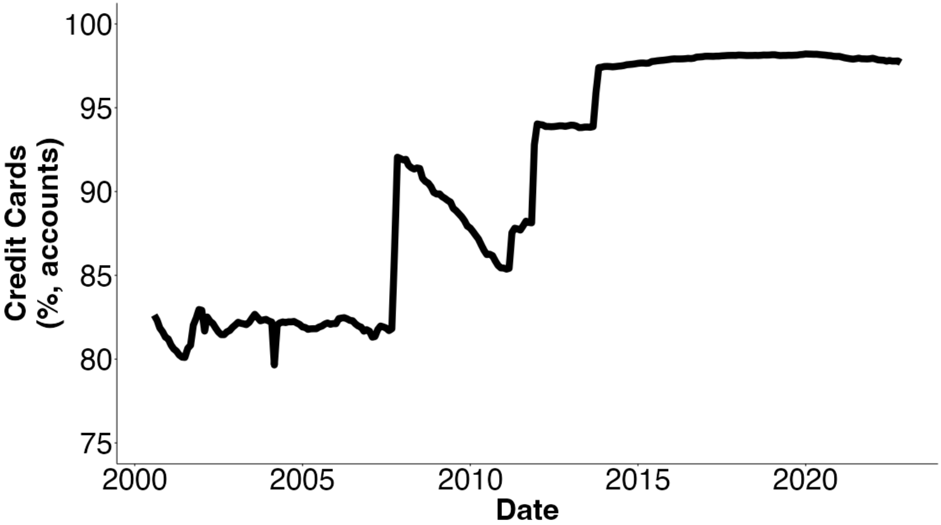
- Regulatory: CFPB / Fed / Treasury “require” reporting as done with credit limits.
  (via ‘soft’ supervisory power or ‘hard’ law)

Understanding Credit Reporting

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

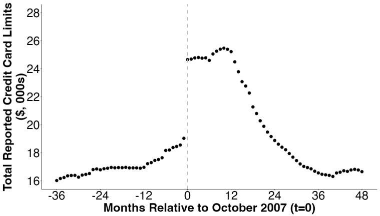
1. Market effects of reporting (efficiency, strategic reactions, competition).
2. Effects on consumer outcomes (credit score, credit access).
3. A new source of exogenous variation other researchers can use more broadly.
4. Clean empirical application of seminal theoretical finance literatures on (i)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

Credit Card Credit Limit Reporting

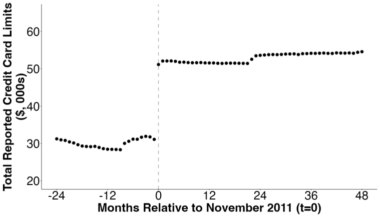


3 Events of Lenders Starting Reporting of Credit Card Credit Limits

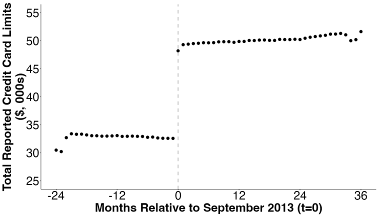
2007
14.00 mn



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:

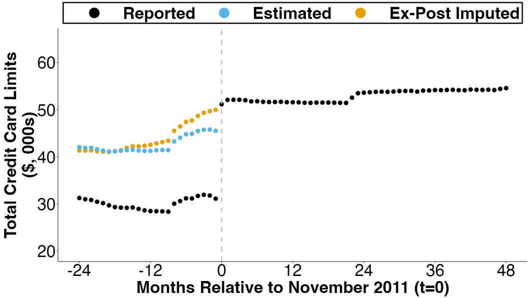
1. Consumers' behavioral type.
2. Credit limit their competitors (who have private information) are willing to extend.

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

Credit Card Credit Limits

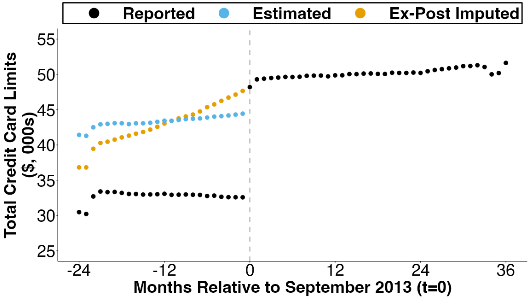
2011

12.85 mn consumers



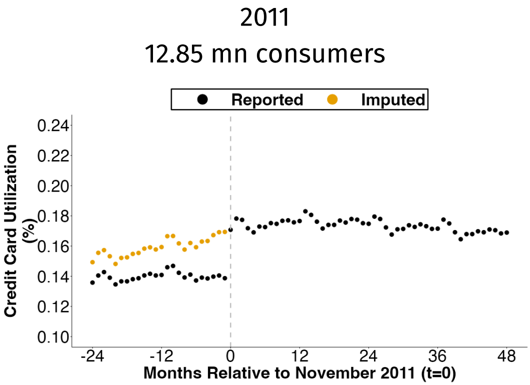
2013

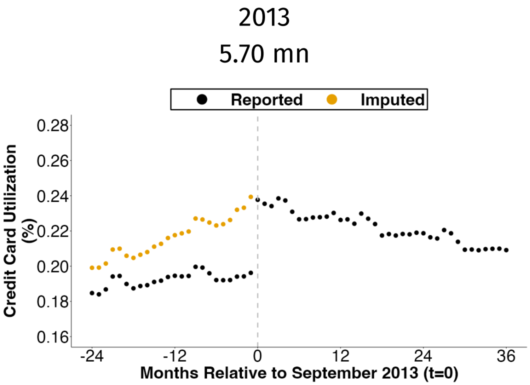
5.70 mn



- **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.

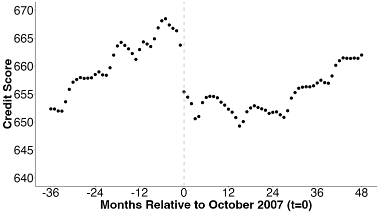
Credit Card Utilization



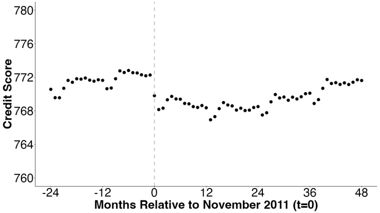


Credit Score

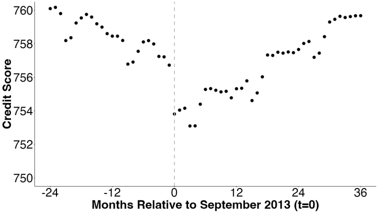
2007
14.00 mn consumers



2011
12.85 mn consumers



2013
5.70 mn

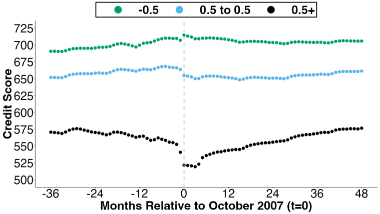


- Lower score as more utilized than observed using highest historical statement balance.
- Must mean highest historical statement balance > current credit limit.
- i.e. Limits on these cards declined (on average). Makes sense given crisis timing.

Credit Score

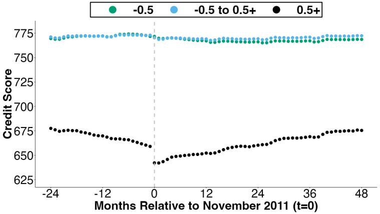
2007

14.00 mn consumers



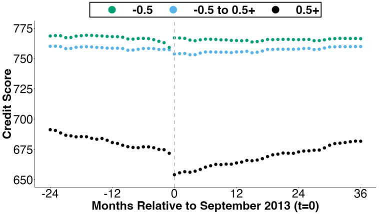
2011

12.85 mn consumers



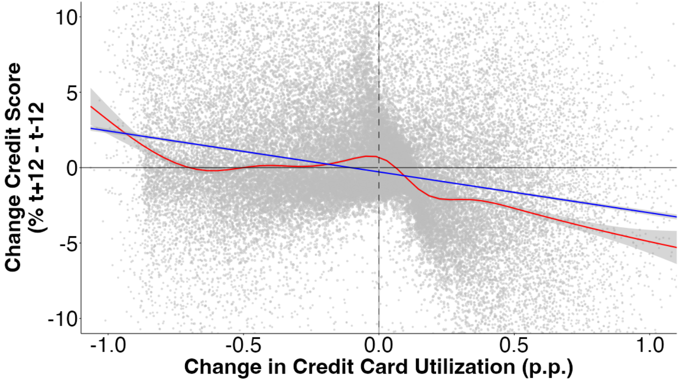
2013

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



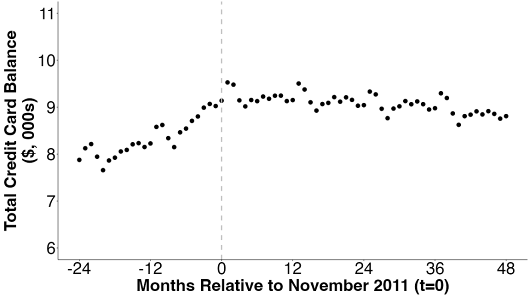
HTE by change in utilization: $\frac{Balance_{t-1}}{CreditLimit_t} - \frac{Balance_{t-1}}{HighBalance_{t-1}}$

i.e. how much *new* information

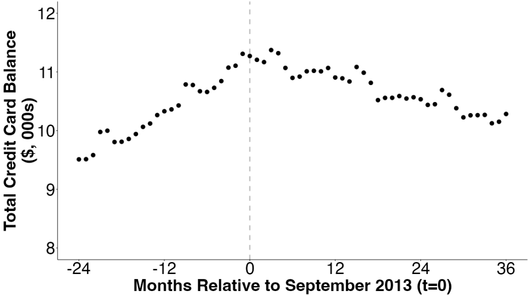
- will do other HTE cuts (e.g. \$ limits, portfolio utilization, credit score).

Credit Card Statement Balance

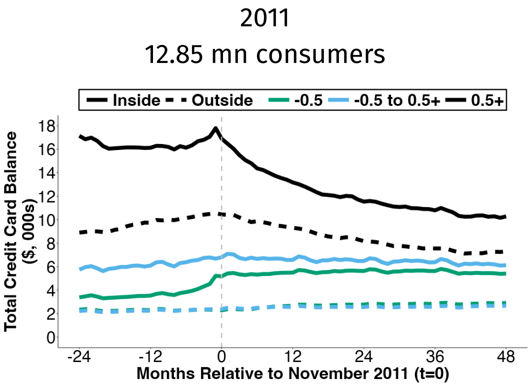
2011
12.85 mn consumers

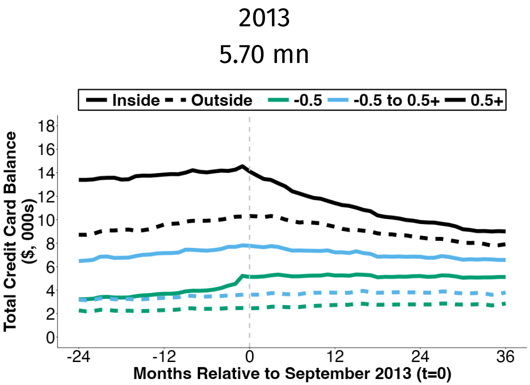


2013
5.70 mn



Credit Card Statement Balance



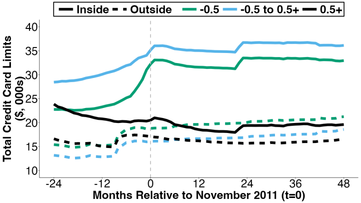


- HTE by change in utilization: $\frac{Balance_{t-1}}{CreditLimit_t} - \frac{Balance_{t-1}}{HighBalance_{t-1}}$
- **Inside:** Lenders who started reporting credit limits. **Outside:** All other lenders.

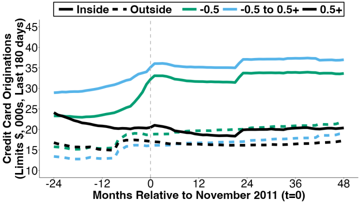
Credit Card Credit Limits

2011

Credit card limits (portfolio).

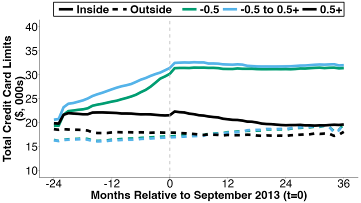


Credit card limits (originations).

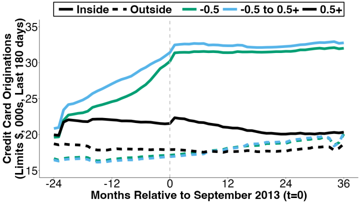


2013

Credit card limits (portfolio).



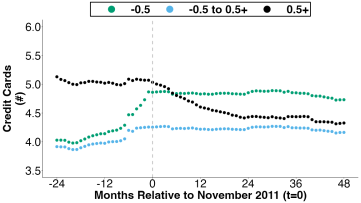
Credit card limits (originations).



Number Credit Cards

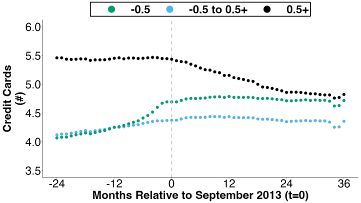
2011

Number credit cards (portfolio).

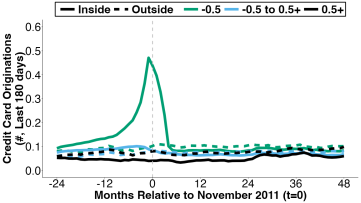


2013

Number credit cards (portfolio).



Number credit cards (originations).



Number credit cards (originations).