Unraveling Information Sharing in Consumer Credit Markets

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TransUnion, 14 May 2024

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Breakdown Of Information Sharing

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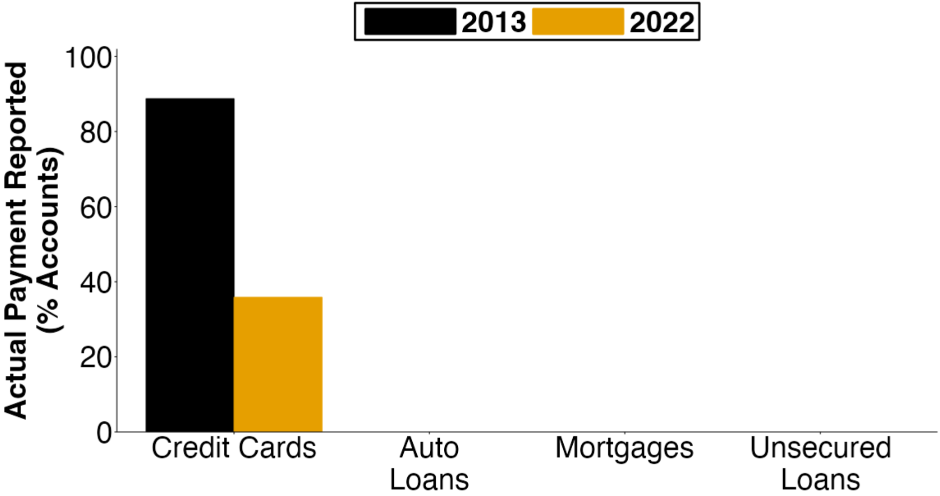
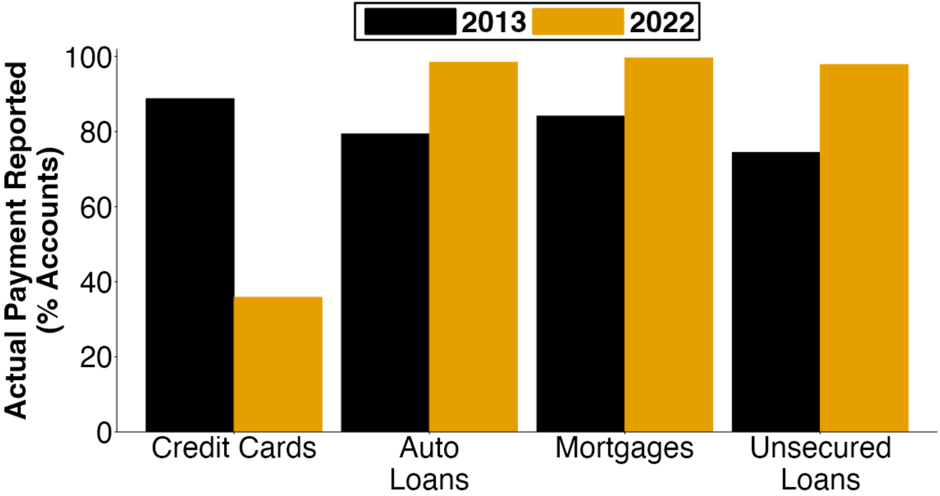


Breakdown Of Information Sharing For Credit Cards But Not For Other Products



Key Contributions

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    - Information sharing sensitive to innovations enabling targeting profitable customers
      (e.g., Diamond, 84; Ramakrishan & Thakor, 84; Pagano & Japelli, 93; Raith, 96; Bouckaert & Degryse, 06; Bergemann & Bonatti, 19; Jones & Tonetti, 20)

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Why is information is missing from US consumer credit reports?

Four Parts to Paper

1. Unraveling Information Sharing
2. Consumer Credit Profitability
3. Selection in Credit Card Lenders Sharing Information
4. Effects of Mandating Information Sharing

Data: Anonymized sample of US consumer credit reports

Part 1. Unraveling Information Sharing

Describe breakdown of sharing information
on actual payments in US consumer credit markets

Innovation ("Trended Data")

- Enables targeting profitable customers by credit card behaviors:
  - spending (driving interchange revenue)
  - revolving debt (driving interest revenue)

Difference-in-differences: innovation $\rightarrow$ information sharing $\downarrow$

Predict profitability in credit cards, auto loans, & unsecured loans

Actual payments information $\rightarrow$ predicting lifetime profits $\uparrow$ for credit cards, but not for auto or unsecured loans

- $+31\%$ interchange revenue net of rewards
- $+4\%$ financing charges (interest $+$ fees) net of charge-offs

Higher profitability & higher spending lenders stop sharing

- Spending: +31% mean & +41% variance

Difference-in-differences: innovation $\rightarrow$ switching $\uparrow$

- +13% new credit cards openings

Part 4. Effects of Mandating Information Sharing: Evidence from Credit Card Limits

Difference-in-differences: sharing credit card limit information

- $+23$ point credit score
- $\uparrow$ competition with substitution from inside to outside lenders

1.Unraveling Information Sharing

Data: University of Chicago Booth's TransUnion Consumer Credit Panel

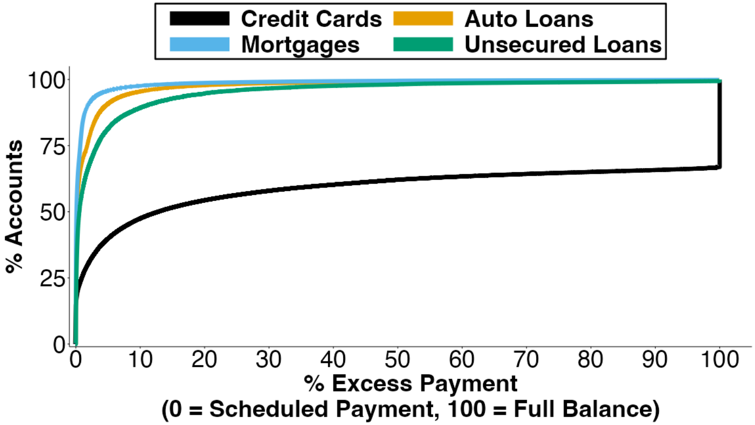
- Anonymized US consumer credit reporting data from TransUnion
- Sample of 1 in 10 consumers with US credit reports
- Monthly, individual credit tradelines + consumer-level data (e.g., credit scores)
- Apply standard data cleaning steps
  (Gibbs, Guttman-Kenney, Lee, Nelson, van der Klaauw, & Wang, 2023 for *JEL*)
- Study 84 credit card furnishers (92% market share) observed 2012 to 2015, top 6 (66%)

No individual firms are identified in these data

Example Credit Report: Credit Card Tradeline Information

Month	Credit Limit	Balance	Scheduled Payment	Actual Payments	Payment Status
1	$20,000	$2,700	$53	$2,700	OK
2	$20,000	$2,200	$43	$2,700	OK
3	$20,000	$2,700	$53	$2,200	OK

For Credit Cards, Actual Payments Often Differ from Scheduled Payment



$$\% \text{ Excess Payment} = \frac{\text{Actual Payments - Scheduled Payment}}{\text{Balance - Scheduled Payment}}$$

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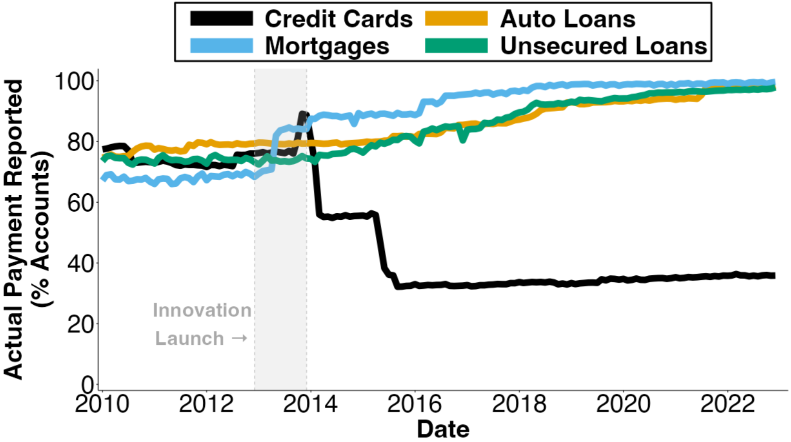
3	$20,000	$2,700	$53	$2,200	OK
4	$20,000	$2,300	$46	$0	OK
5	$20,000	$5,200	$104	$0	OK
6	$20,000	$8,700	$174	$0	OK

Credit card lenders stop sharing actual payments information with credit bureau

Credit Cards ↓ Sharing Actual Payments, Other Credit Products ↑ Sharing



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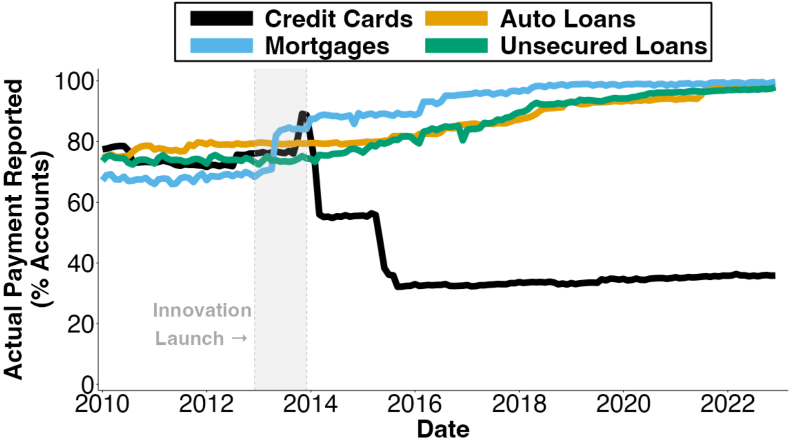
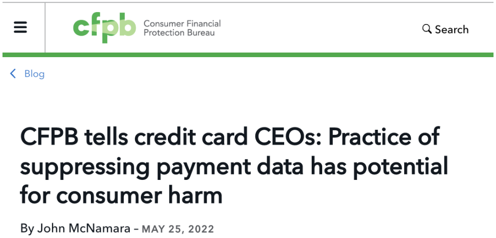


165 million US consumers missing credit card actual payments information

Policy-Relevant Topic


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

Consumer Financial Protection Bureau (CFPB) documents:

Non-Sharers are the 6 largest credit card lenders:
American Express, JPMorgan Chase, Citibank, Bank of America, Capital One, Discover

- 2 never share
- 1 stopped sharing in 2014
- 3 later stopped sharing (1x 2014, 2x 2015)

"None plan to furnish actual payments information voluntarily"

Innovation

Credit Bureau Innovation Launched from 2013: "Trended Data"

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

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Trended Data creates bundle of variables using credit reports over time (trends!)
– especially combining actual payments with balances

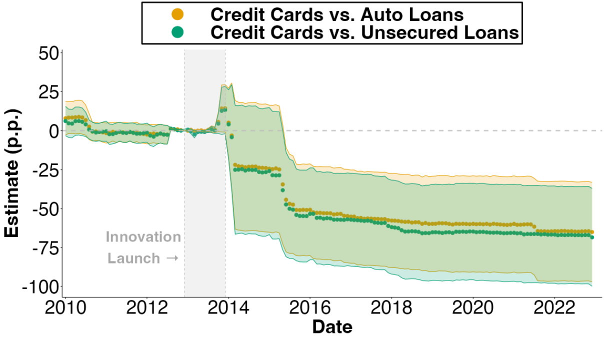
"The most important tool developed...since the credit score" – Credit Card Risk Director

"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

Difference-in-Differences Effect of Trended Data on Information Sharing

Credit cards more exposed as use for pre-selected marketing of credit card behaviors

↓ 65 p.p. (s.e. 16) in sharing actual payments on credit cards vs. auto loans



$$Y_{p,t} = \sum_{\tau \neq \text{Dec 2012}} \delta_\tau \left(D_\tau \times CRED_p \right) + \gamma_p + \gamma_t + \varepsilon_{p,t}$$

Breakdown Of Sharing Actual Payments Information Is US-Specific

Actual payments data remain shared in UK and Canada post introducing Trended Data

Why?

- **UK** Principles of Reciprocity by industry body Steering Committee on Reciprocity:
  (i) bans use of credit reports for pre-selected marketing to individuals
  (ii) reciprocality in sharing data
- **Canada** limits using credit reports for marketing (e.g., geographic not individual targeting)

Less trade-off of sharing actual payments data in UK or Canada: less risk of targeted marketing

2.Consumer Credit Profitability

Credit card profitability depends on ex-post consumer behaviors: multiple dimensions of information asymmetry & revenue streams

t = 1:

- \$1,000 new spending ($\rightarrow$ generates \$5 interchange revenue net of rewards)
- \$1,000 statement balance & \$10 minimum payment due

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- \$250 actual payments

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- \$1,000 - \$250 = \$750 revolving debt ($\rightarrow$ generates interest revenue but risk of charge-off)
- \$12 interest + \$30 fee = \$42 financing charges

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- \$12 interest + \$30 fee = \$42 financing charges
- \$2,000 new spending ($\rightarrow$ generates \$10 net interchange revenue)
- \$2,792 statement balance & \$70 minimum payment due

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$$\textit{revolving debt}_t = \textit{statement balance}_{t-1} - \textit{actual payments}_t$$

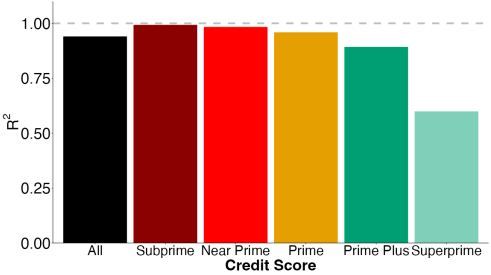
$$\textit{spending}_t = \textit{statement balance}_t - \textit{statement balance}_{t-1} + \textit{actual payments}_t$$

If *actual payments$_t$* unobserved, ↑ noise to measuring spending & revolving debt

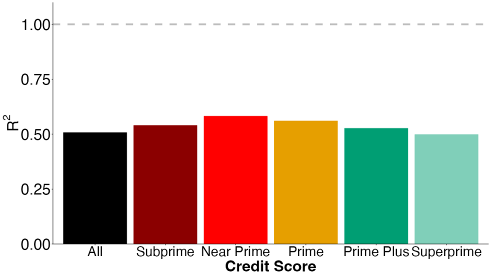
R^2 from OLS regressions using Dec 2013 data on statement balances

Evaluate relative to $R^2 = 1$ *if actual payments$_t$* observed

Revolving Debt: $R^2 = 0.94$ (0.60 Superprime)



Spending: $R^2 = 0.51$



Noise impedes targeting of pre-selected credit card offers

Bad news for academics & policymakers measuring revolving debt or consumption

Lifetime Profits in Consumer Credit Markets

Lenders predict profitable types to target marketing

$$\Pi^{CRED}_{PRE} = E_{t=0}[\Pi^{CRED}_{POST}|X_0] = E_{t=0}\Big[\sum_{t=1}^{T}\delta^t\Big(i_t + \alpha\ r_t + f_t - c_t\Big)|X_0\Big] - a$$

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Measuring in data

- **Auto Loans and Unsecured Loans:**
  Scheduled financing charges adjusted for ex-post prepayments and charge-offs

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Measuring in data

- **Auto Loans and Unsecured Loans:**
  Scheduled financing charges adjusted for ex-post prepayments and charge-offs
- **Credit Cards:**
  Estimate financing charges from minimum payments
  Assume interchange net of rewards is 0.5% of spending

Develop New Methodology for Estimating Financing Charges

Minimum payment (M_t) determined by: $M_t = \max\{\$\mu,\ \theta\%\ b_t + r_t + f_t\}$

Infer $\$\mu$ and $\theta\%$ for each furnisher from (1) minimum payment (2) statement balance

Observed minimum payment $-$ *predicted* minimum payment $=$ financing charges

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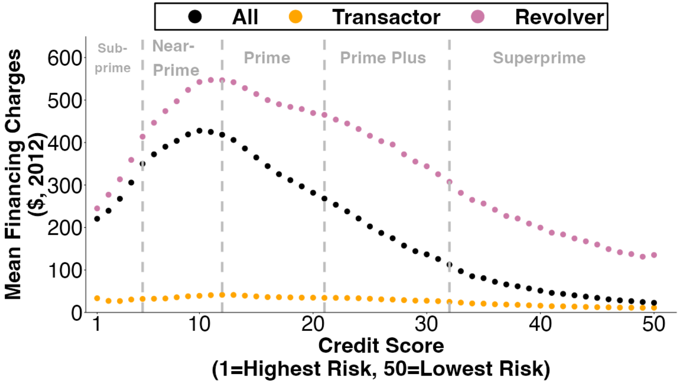


Marginal Value of Actual Payments for Predicting Profits

1. **No Actual Payments Data:** 100 credit score quantiles, and credit score interacted with other account-level information up to three years of balances, delinquency, utilization rates, estimated financing charges, card tenure, and credit limits

$$Y_{i,2012+j} = X'_{i,2012}\beta + \varepsilon_{i,2012+j} \tag{1}$$

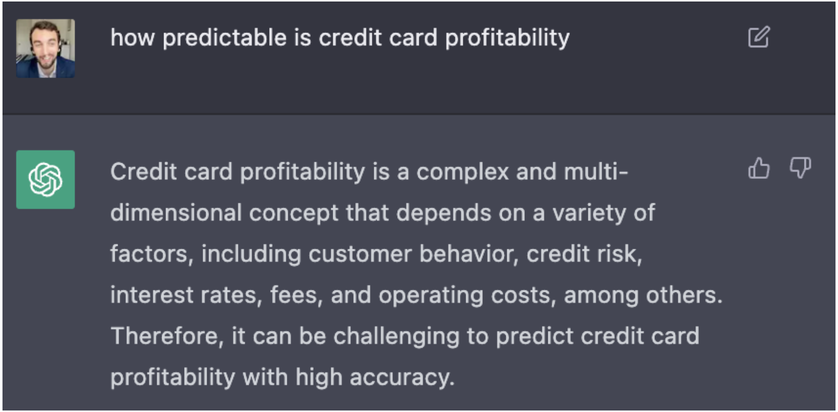
2. **With Actual Payments Data**: Model 1 + actual payments data interactions

$$Y_{i,2012+j} = X'_{i,2012}\beta + Z'_{i,2012}\lambda + \varepsilon_{i,2012+j} \tag{2}$$

Use data to December 2012 to predict outcomes 2013 to 2022

Evaluate by out-of-sample R^2

Predicting Credit Card Profitability is Hard!

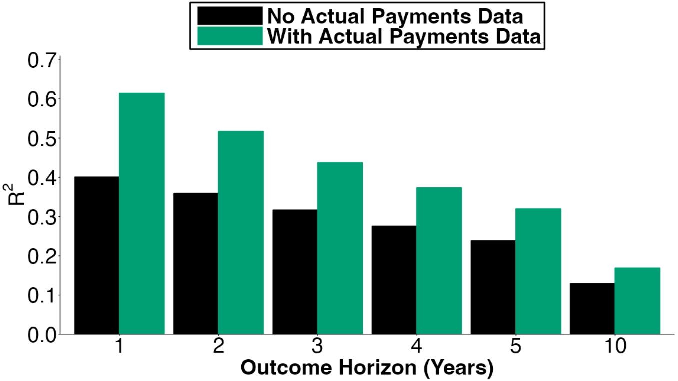


Actual Payments ↑ Predicting Profits On Credit Cards ($R^2 : +4\%$) But Doesn't Improve Predicting Profits for Auto or Unsecured Loans

Out-of-Sample R^2 Predicting Lifetime Profits

Model	Credit Cards	Auto Loans	Unsecured Loans
1. No Actual Payments Data	0.1919	0.1925	0.3508
2. With Actual Payments Data	0.2003	0.1928	0.3511

Actual Payments Data ↑ Predicting Interchange Net of Rewards (R^2: +31%)



1 year

R^2: 0.401 → 0.614

Portfolio value: +24%

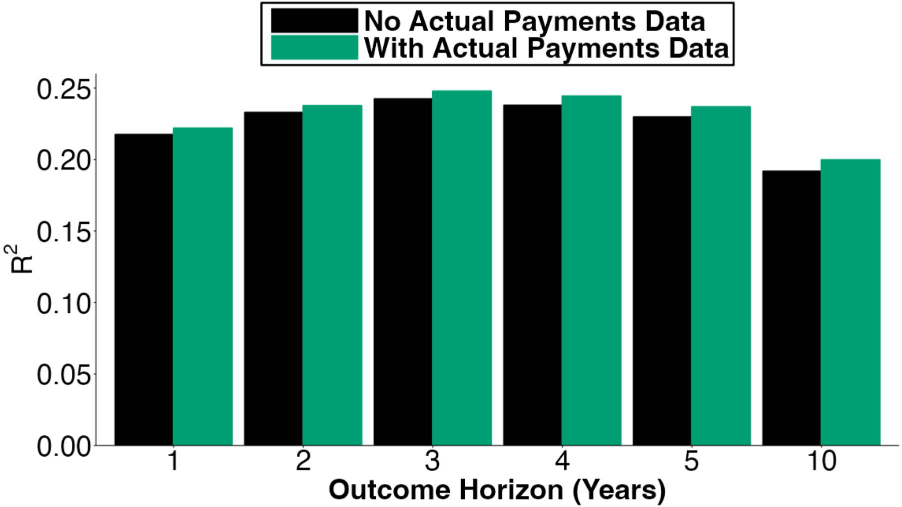
10 year

R^2: 0.129 → 0.169

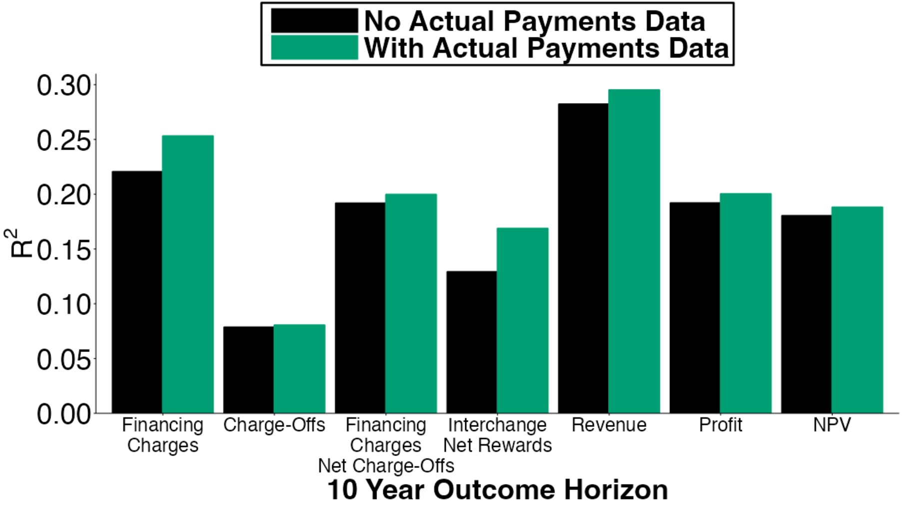
Portfolio value: +13%

Portfolio value of top 100,000 cards ranked by out-of-sample predictions

Actual Payments Data ↑ Predicting Financing Charges Net Charge-Offs (R^2: +4%, Portfolio: +1%)



Actual Payments Data ↑ Predicting Profitability (R^2: +4.2%, Portfolio: +2.7%) Especially Interchange Component



Recap Of Key Findings So Far

- Breakdown of sharing actual payments data for US credit cards but not other products
- Timing due to credit bureau innovation revealing private credit card behaviors:
  - spending (driving interchange revenue)
  - revolving (driving interest revenue)
- Actual payments doesn't predict auto loan or unsecured loan profits
- Actual payments predicts credit card profits
  - especially spending driving interchange revenue net of rewards

3.Credit Card Lender Selection

Revealing Credit Card Behaviors Heterogeneously Affects Lenders

Examine selection of lenders to inform motivations for sharing decisions

- Default Risk Doesn't Explain
- Non-Default Behaviors: (a) Revolving (b) Spending

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Credit card lenders' business models vary in reliance on interchange revenue:

	American Express	**Capital One**
Interchange Revenues (% Revenues)	55%	27%
Net Interchange Revenues (% Net Revenues)	68%	18%
Marketing Costs	\$5.5 bn	\$4.0 bn

Sources: American Express & Capital One Annual Accounts

Marketing large expense for all lenders

Unraveling Driven By Some Credit Card Lenders Stopping Sharing

Lender Classification	**% 2012 Cards**
Always: Share information in 2012 & 2015	18%
Stoppers: Share information in 2012 but not 2015	47%
Nevers: Never share information in 2012 & 2015	32%

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Always worst residual types remain sharing information (Akerlof-esque)

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Lenders' Responses to CFPB (2023):

Stoppers:

- Firm 4: "Doesn't believe benefits outweigh proprietary interests"
- Firm 6: "Other major issuers were no longer providing...left at competitive disadvantage"

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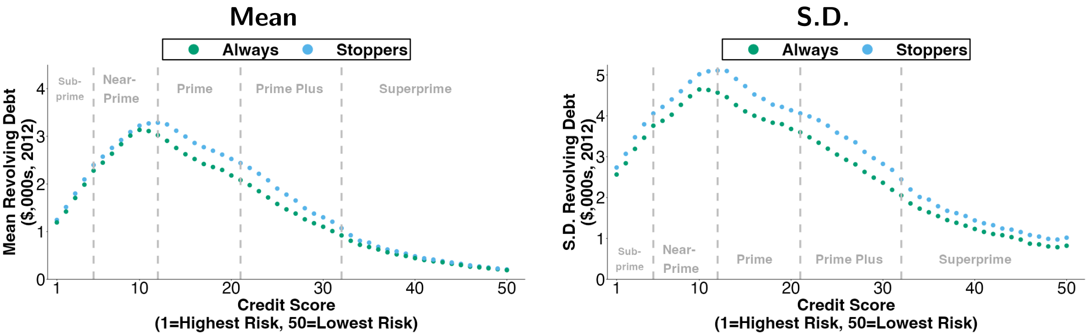
- Firm 6: "Other major issuers were no longer providing...left at competitive disadvantage"

Nevers:

- Firm 1: "Not required to do so. Not consistently furnished nor adequately studied"
- Firm 5: "Not required, furnishing is voluntary. Doesn't believe cost...is worth it"

Revolving Debt Higher for Lenders who Stop Sharing

Mean (S.D.) Residual Revolving Debt: **Stoppers** \$1,708 (\$3,414), **Always** \$1,538 (\$3,048)

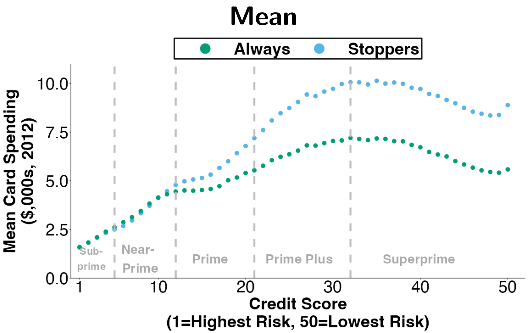


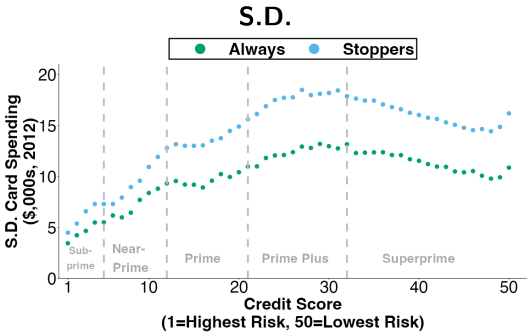
N.b. Fixed thresholds for credit score quantiles across all groups and charts

Financing charges net of charge-offs for **Stoppers** +36% mean, +8% higher S.D. vs. **Always**

Spending Explains Differential Sharing Decisions

Stoppers' residual spending is +31% ($1,643) higher mean, +41% ($4,275) S.D. than **Always** (mean $5,246, S.D., $10,345)



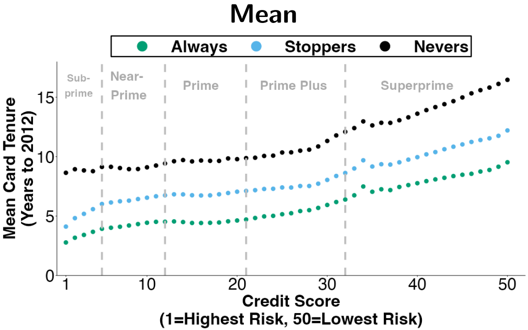


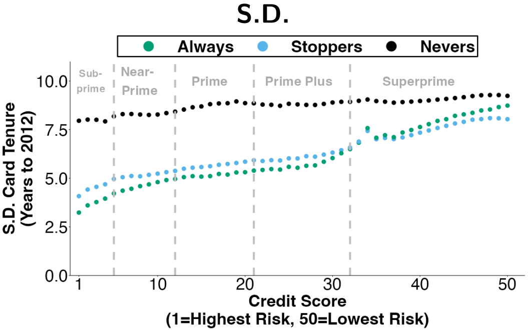
Comparing to aggregate Federal Reserve data indicates **Nevers** > **Always**+**Stoppers**

Card Tenure Varies Across & Within Credit Score, Across Lenders

Mean (S.D.) Card Tenure Months:

Nevers 136.5 (106.0), **Stoppers** 97.6 (75.5), **Always** 71.0 (73.8)

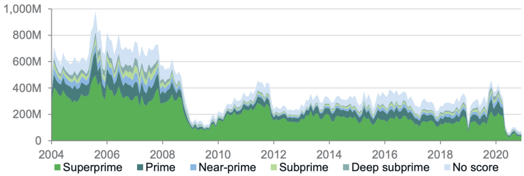




Why Lend To High Credit Score Transactors (Little-To-No Financing Charges)?

60% credit card accounts high credit scores

Credit Card Offers Mainly Superprime



Source: CFPB (2021)

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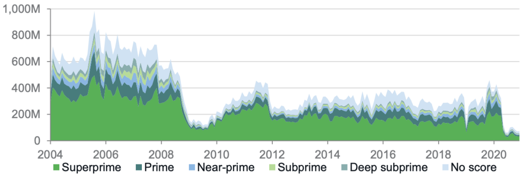
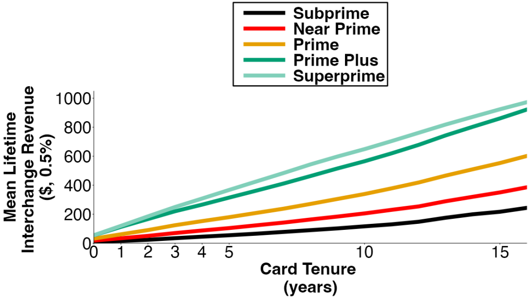
60% credit card accounts high credit scores

Credit Card Offers Mainly Superprime



Source: CFPB (2021)

Lifetime Interchange Revenue By Card Tenure & Credit Score



Average transactor may have "low" net revenues each year...but longer tenure means $NPV > 0$

Mean cost to acquire new account $140 (range $50–$390) (R.K.Hammer, 2012)

Difference-in-Differences: Effects of Innovation On New Credit Card Openings

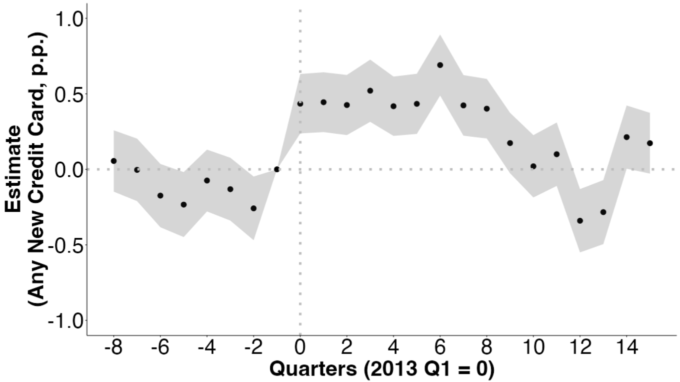
Exposure Measure: % consumer's card balances in Dec 2012 where actual payments **shared**:

$$EXPT_i \equiv \frac{\sum_c 1\{F_c \in \textbf{Sharers}\} \times b_{i,c}}{\sum_c b_{i,c}}$$

Balanced panel of 0.5 mn consumers 2011 to 2016

Innovation Caused ↑ Account Openings

Outcome: Any New Credit Card Opened (t-1 mean: 3.2%)



$$Y_{i,t} = \sum_{\tau \neq -1} \delta_\tau \left(D_\tau \times EXPT_i \right) + \gamma_i + \gamma_t + \varepsilon_{i,t}$$

Recap Of Key Findings So Far

- Breakdown of sharing actual payments data for US credit cards but not other products
- Timing due to credit bureau innovation revealing private credit card behaviors:
  - spending (driving interchange revenue)
  - revolving (driving interest revenue)
- Actual payments doesn't predict auto loan or unsecured loan profits
- Actual payments predicts credit card profits
  - especially spending driving interchange revenue net of rewards
- Adverse selection in sharing
  - Higher mean and variance spending, revolving debt, financing charges
  - Longer tenure
- Innovation was competitive threat to profitable incumbents
  - $\uparrow$ switching prompted $\downarrow$ sharing information

4. Effects of Mandating Information Sharing

Institutional Background

- 1990s mostly *not* sharing credit limit information
  → Regulatory pressure and threats by agencies to restrict access
- 2000s most **but not all** lenders sharing credit limit information (Hunt, 05)
  → Federal Trade Commission (FTC) rules mandates sharing credit limit information
- Full coverage in 2010s

Effects of Mandating Information Sharing: Evidence from Credit Card Limits

Institutional Background

- 1990s mostly *not* sharing credit limit information
  → Regulatory pressure and threats by agencies to restrict access

- 2000s most **but not all** lenders sharing credit limit information (Hunt, 05)
  → Federal Trade Commission (FTC) rules mandates sharing credit limit information

- Full coverage in 2010s

How credit limits matter

- 20% to 30% of credit score is credit utilization $= \frac{\text{statement balance}}{\text{credit limit}}$

- If no credit limit shared, use highest historical account balance
  → Typically overstates utilization
  → Consumers appear riskier to outside lenders

Difference-in-Differences for Causal Effects of Mandating Information Sharing

Consumer-level exposure: Difference between the *revealed* credit limits ($r_i \equiv \sum_c r_{i,c}$) and credit limits that could be previously *inferred* ($h_i \equiv \sum_c h_{i,c}$)

$$EXPL_i = \frac{r_i - h_i}{r_i}$$

Difference-in-Differences for Causal Effects of Mandating Information Sharing

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$$EXPL_i = \frac{r_i - h_i}{r_i}$$

$\uparrow EXPL_i \rightarrow \downarrow$ utilization $\rightarrow \uparrow$ credit score

Difference-in-Differences for Causal Effects of Mandating Information Sharing

Consumer-level exposure: Difference between the *revealed* credit limits ($r_i \equiv \sum_c r_{i,c}$) and credit limits that could be previously *inferred* ($h_i \equiv \sum_c h_{i,c}$)

$$EXPL_i = \frac{r_i - h_i}{r_i}$$

$\uparrow EXPL_i \rightarrow \downarrow$ utilization $\rightarrow \uparrow$ credit score

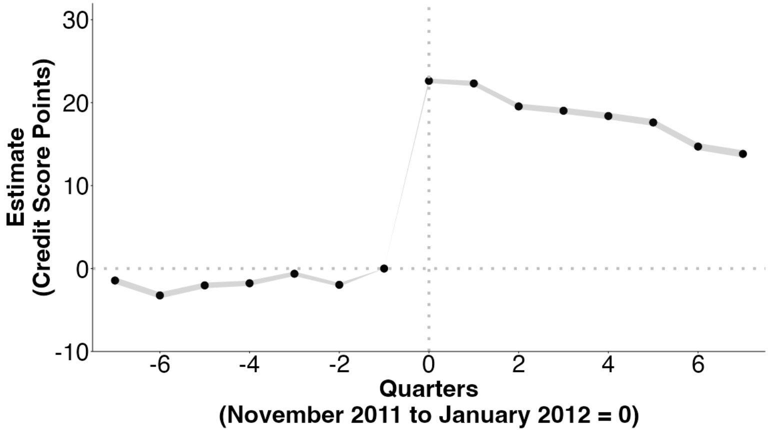
Difference-in-Differences with Varying Treatment Intensity

Balanced panel of 1.1 mn consumers. Clustering at consumer-level.

$$Y_{i,t} = \sum_{\tau \neq \text{-}1} \delta_\tau \left(D_\tau \times EXPL_i \right) + \gamma_i + \gamma_t + \varepsilon_{i,t}$$

Information Revelation ↑ Credit Scores

Difference-in-Differences Estimate ↑ 22.6 [22.4, 22.9] on mean 776 (t-1)



Information Revelation ↑ Competition

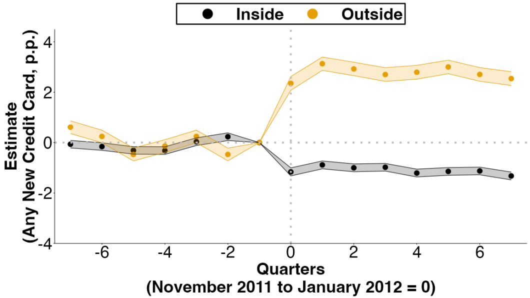
Outcomes by **inside** and **outside** lenders

Information Revelation ↑ Competition

Outcomes by **inside** and **outside** lenders

Any New Credit Cards Opened

−56% inside, +32% outside



Information Revelation ↑ Competition

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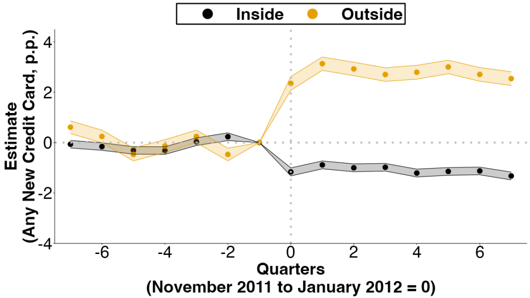
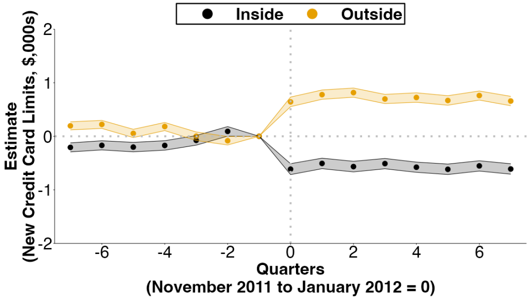


Credit Limits of New Credit Cards Opened

−90% inside, +48% outside



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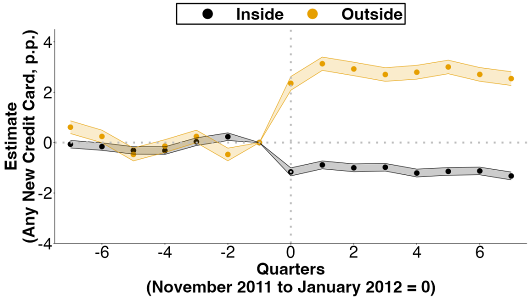

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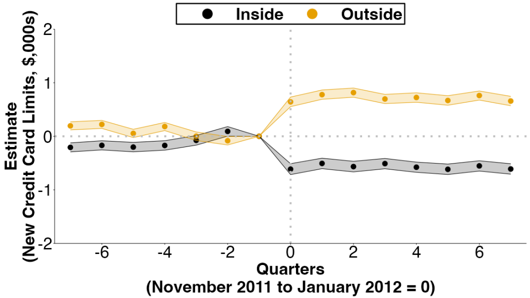

↑ competition desirable in credit card market given

persistently high market concentration & high returns on assets (in excess of risk)

Conclusions

1. **Empirically document fragility of information sharing in highly developed market**
   - Breakdown of information sharing an unintended response to innovation
   - Information sharing sensitive to innovations enabling targeting profitable customers
   - Supports policy mandating information sharing
2. **Two new insights on credit card market: importance of spending and card tenure**
   - Spending a 2^{nd} source of uncertainty separate to default risk
   - Card tenure varies across and within credit score $\rightarrow$ need to measure lifetime profits
   - High credit score cards can be profitable from interchange over lifetime

Thank you!

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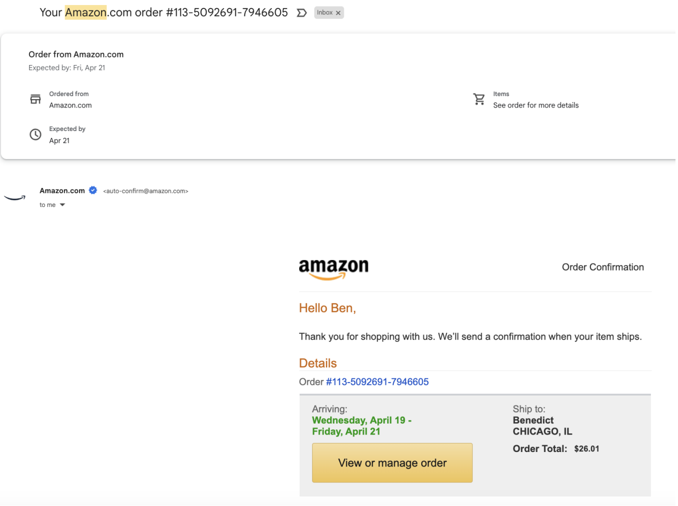
My Research Agenda

1. **Economics of Credit Information**
   - Job Market Paper
   - Paper for *Journal of Economic Literature*
   - "Disaster flags" masking defaults during natural disasters
   - How years of credit visibility impacts future credit access (work-in-progress)
2. **Behavioral Household Finance**
   - Effects of payday loans on consumers (*Review of Financial Studies*)
   - 3 papers testing nudging consumers to reduce credit card debt / studying Autopay
   - Effects of paternalistic policy $\uparrow$ credit card minimum payments (work-in-progress)
   - Short paper on buy now, pay later (BNPL)
   - Dynamics of budging heuristics (work-in-progress)

3 Examples of Firms Stopping Sharing Information

1. Amazon Stops Sharing Order Details



3 Examples of Firms Stopping Sharing Information

1. Amazon Stops Sharing Order Details
2. Apple Stops Sharing Location Data

MARKETS BUSINESS INVESTING TECH POLITICS CNBC TV INVESTIN

TECH

Apple’s ad privacy change impact shows the power it wields over other industries

PUBLISHED SAT, NOV 13 2021•11:28 AM EST | UPDATED SAT, NOV 13 2021•11:30 AM EST

3 Examples of Firms Stopping Sharing Information

1. **Amazon Stops Sharing Order Details**
2. **Apple Stops Sharing Location Data**
3. **Twitter Stops Sharing API for Free**

What connects these?

Incumbents Stop Sharing Information $\rightarrow$ Limit Potential Disruptive Innovations

Selection markets with heterogeneous consumers where ability to target drives profits

- t = 0: Incumbent firms with market power from informational rents share data
- t = 1: New technological innovation potentially threatened incumbents
- t = 2: Incumbents respond by $\downarrow$ information sharing to foreclose on (potential) entrants

Incumbents Stop Sharing Information $\rightarrow$ Limit Potential Disruptive Innovations

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3 Examples

1. Amazon Stops Sharing Order Details

- Response to scraping technology

2. Apple Stops Sharing Location Data

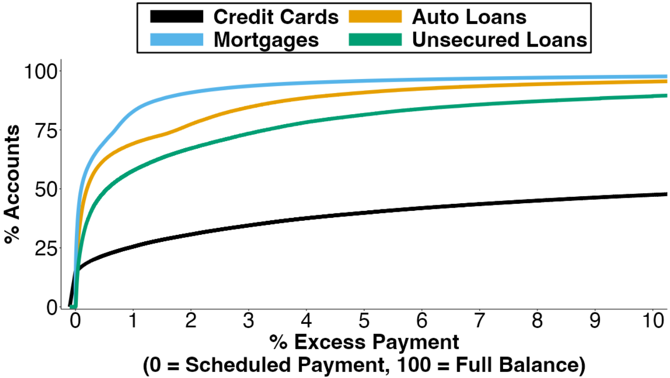
- Response to tracker technology

3. Twitter Stops Sharing API for Free

- Response to ChatGPT technology

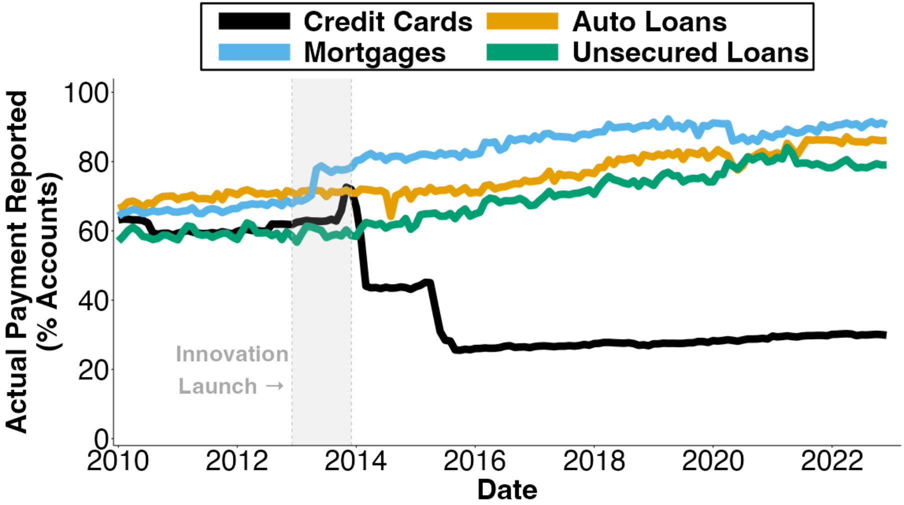
CDF Excess Payment: Actual Payments Relative to Scheduled Payments

Excess Payment Less Than 10%:



$$\% \text{ Excess Payment} = \frac{\text{Actual Payment Amounts - Scheduled Payment Amounts}}{\text{Balance}}$$

Robustness



Credit Cards
Auto Loans
Mortgages
Unsecured Loans
Actual Payment Reported
(% Accounts)
100
80
60
40
20
0
Innovation
Launch →
2010
2012
2014
2016
2018
2020
2022
Date

Institutional Details: Consumer Credit Reporting 🚀

How do lenders use consumer credit reporting data?

- Credit risk (underwriting, account management), marketing & screening (pre-selected offers)

What are the terms for lenders sharing information?

- Voluntary. Non-reciprocal data access. Consumer Data Industry Association facilitates
- If share, Fair Credit Reporting Act (FCRA) requires "accurately" & "with integrity"

Why do lenders voluntarily share information?

- **Regulatory pressure:** FCRA guidance *"encourages voluntary furnishing of information"*
- **Adverse selection & moral hazard** (e.g., Pagano & Japelli, 1993; Padilla & Pagano, 2000)
- **Sequential banking** (e.g., Bizer & DeMarzo, 1992; De Giorgi et al., 2023)
- **Limit scope of entry** (e.g., Bouckaert & Degryse, 2006)

Lenders trade-off potential benefits vs. costs of revealing private information

"Trended Data" Launch Is Technological Advance $\uparrow$ Information From Data

Technically lenders could construct from raw data

In practice they did not. Why not?

Technological constraints: E.g., Equifax (2013)

- "Took us time just to build the infrastructure to house the data"

Legal constraints:

- Compliance concerns prevented lenders constructing trended data

Cost constraints:

- Constructing Trended Data would mean purchasing 12+ archives

Trade-offs of information sharing

Lender Trade-Offs

Benefits	Costs
Technology	Short-Run Targeting
Reduce Information Asymmetries	Long-Run Increased Competition

Benefits < Costs for some segments e.g., buy now pay later (BNPL) & payday lenders

Trade-Offs for Credit Reporting Agency:

- Use technology to produce data products to sell to lenders
- Incentive compatibility constraint for lenders to share information

Market Failures

Negative Externality for Non-Credit Card Markets

- Credit card behaviors using actual payments information predict non-credit card default

- Misallocating / mispricing capital
(could be done more efficiently if credit scores observed credit card actual payments)

Market Power in Credit Card Market

- Incumbency advantage: (1) persistent high returns on assets in excess of risk (2) top 6 lenders have two-thirds market share since 2005

- Undermines pro-competitive innovation (more targeted offers / lower acquiring costs)

- Potentially not incentivizing informed consumers to repay credit card debt

Trade-offs of non-reciprocal information sharing

Benefits of Sharing

1. Technology
2. Reduce Information Asymmetries

Costs of Sharing

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

Pre-Trended Data:

Incumbents report data. Why? e.g., firm inertia, fear of regulators, limits scope of entry.

Post-Trended Data:

Adverse selection $\downarrow$, consumer switching costs $\downarrow$ $\Rightarrow$ information sharing $\downarrow$

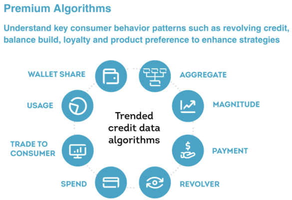
Credit Bureaus Launched Innovation from 2013: “Trended Data”

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

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

- Reveals **credit cards** behaviors
driving profitability beyond delinquency

- Revolving debt
- New spending
- Interest rates



Reveals not just credit risk but who profitable consumers are

How is "Trended Data" used by lenders?

- **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
- **Credit risk**:
  "Including trended data materially improved modeling of loan performance."
  - Fannie Mae (consistent with Equifax, Experian, TransUnion, FICO, & VantageScore)

Why launched then?

- CARD Act limited credit card fees (Agarwal et al., 15) & interest (Nelson, 22)

- Interchange revenues become increasingly important source of credit card revenue

Consumer Credit Score Performance With Actual Payments (AP) Information

Outcome: Any 90+ Days Past Due (DPD)		
Model	**AUROC**	**Accuracy**
1. Credit Score	0.93419	0.88398
2. Credit Score + 1 Year AP Credit Cards	0.94108	0.89108
3. Credit Score + 3 Year AP Credit Cards	0.94540	0.89726

Installment Credit Score Performance With Actual Payments (AP) Information

Outcome: Any Installment Loan 90+ Days Past Due (DPD)

Model	AUROC	Accuracy
1. Credit Score	0.88950	0.86356
2. Credit Score + AP Installment	0.89144	0.86627
3. Credit Score + AP Credit Cards + AP Installment	0.89364	0.86686

Measuring Credit Card Behaviors

OLS regressions for December 2023 for furnishers where actual payments information shared. One observation per account (i).

$$Y_{i,t} = \alpha + \beta_1 \, b_{i,t} + \beta_2 b_{i,t-1} + \beta_3 \tilde{\Delta} b_{i,t} + \beta_4 \mathbf{1}\{b_{i,t} > 0\} + \beta_5 \mathbf{1}\{b_{i,t-1} > 0\} + \varepsilon_{i,t}$$

where $b_{i,t}$ is statement balance for account i at time t

$$\tilde{\Delta} b_{i,t} \equiv \begin{cases} b_{i,t} - b_{i,t-1} & \text{if } b_{i,t} - b_{i,t-1} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

If Know Revolving Debt, Insufficient to Know Spending

Let statement balances be zero: $b_t = b_{t-1} = 0$

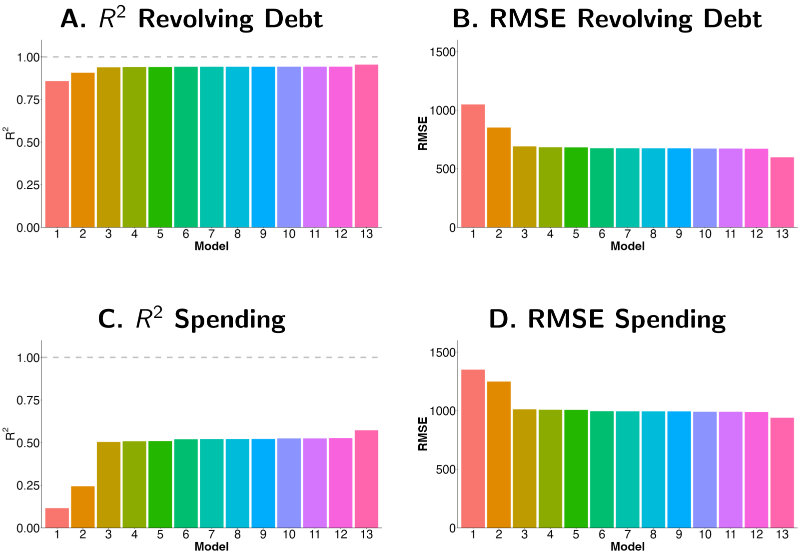
Clearly revolving debt is zero: $d_t = 0$

What is spending? $s_t = b_t - b_{t-1} + p_t = 0 - 0 + p_t$

s_t could be anything: \$0, \$1,000, \$10,000!

N.b. consumers can and do pay more than their statement balance (e.g., pay before statement issued or pay their outstanding balance)

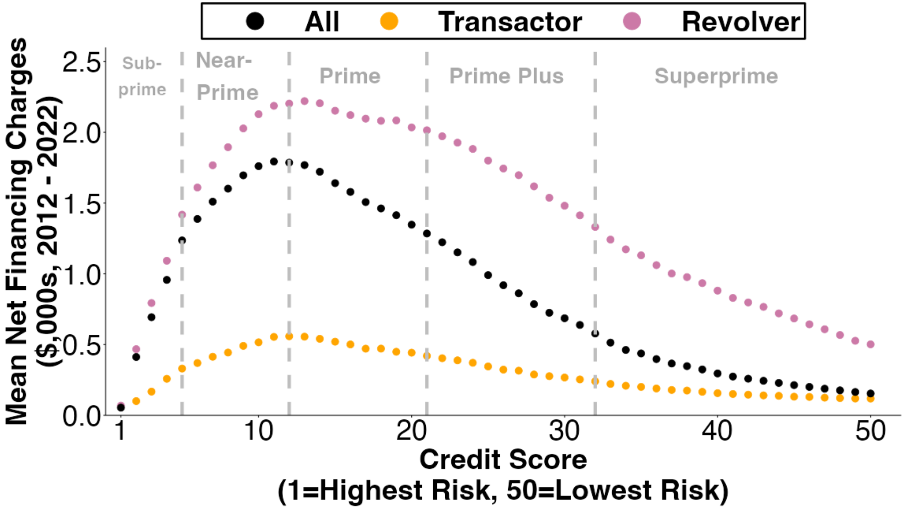
Measurement Error in Credit Card Behaviors



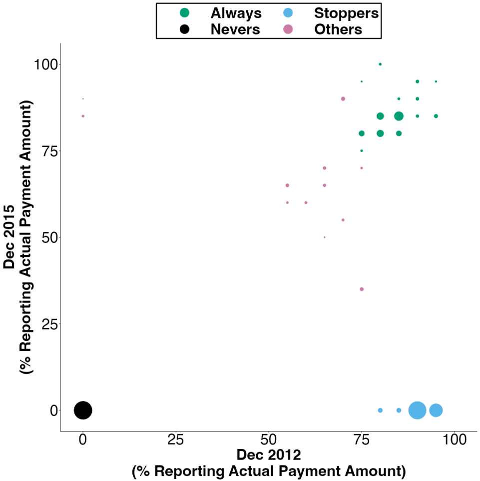
Consumer Credit Profitability Relies on Predicting Consumer Behaviors

	Auto Loans	Unsecured Loans	Credit Cards
Duration	Fixed-Term		Open-Ended
Revenue Streams	Financing Charges (Interest, Fees)		Financing Charges (Interest, Fees), Interchange
Uncertain Behaviors	Delinquency, Prepayment		Delinquency, Revolving Amount & Duration, Spending
Collateral	Secured	Unsecured	

2012 to 2022 Financing Charges Net of Charge-Offs



Classifying Credit Card Lenders By Actual Payment Sharing Decisions



Interchange Stats

Always

1 year: R^2 0.401 $\to$ 0.614

3 year: R^2 0.317 $\to$ 0.437

5 year: R^2 0.239 $\to$ 0.320

10 year: R^2 0.129 $\to$ 0.169

Always+Stoppers

1 year: R^2 0.401 $\to$ 0.614

3 year: R^2 0.317 $\to$ 0.437

5 year: R^2 0.239 $\to$ 0.320

10 year: R^2 0.129 $\to$ 0.169

Portfolio Values

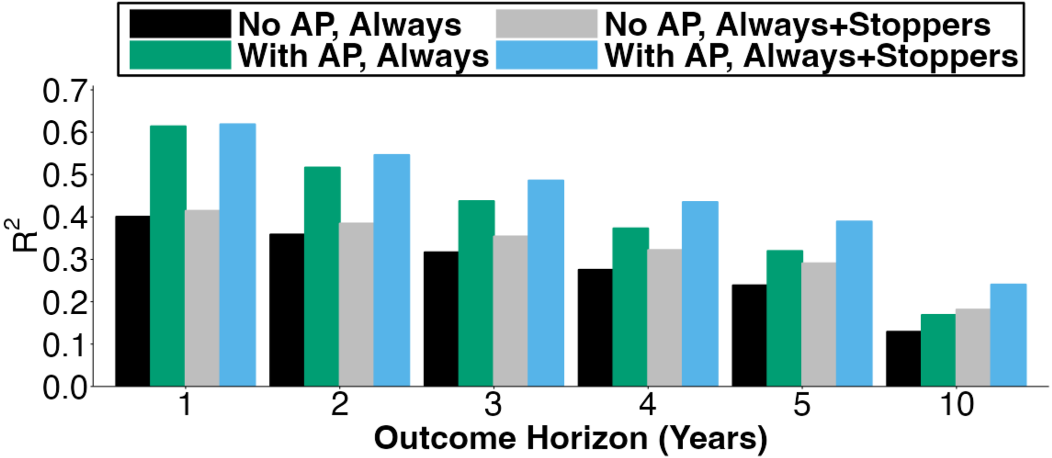
1 year **Always**: +24% (\$171 +\$42)

1 year **Always+Stoppers**: +25% (\$319 +\$80)

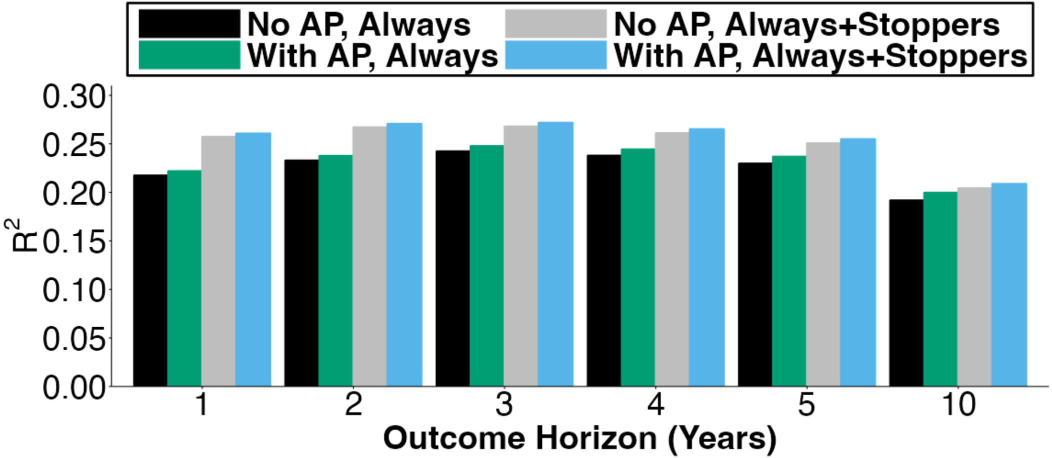
10 year **Always**: +13% (\$473 +\$63)

10 year **Always+Stoppers**: +18% (\$531 +\$96)

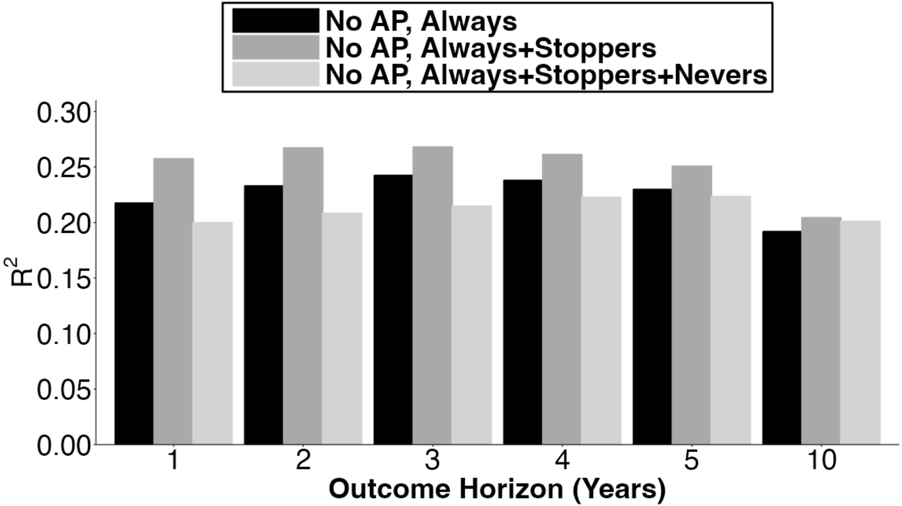
Predicting Interchange Net of Rewards



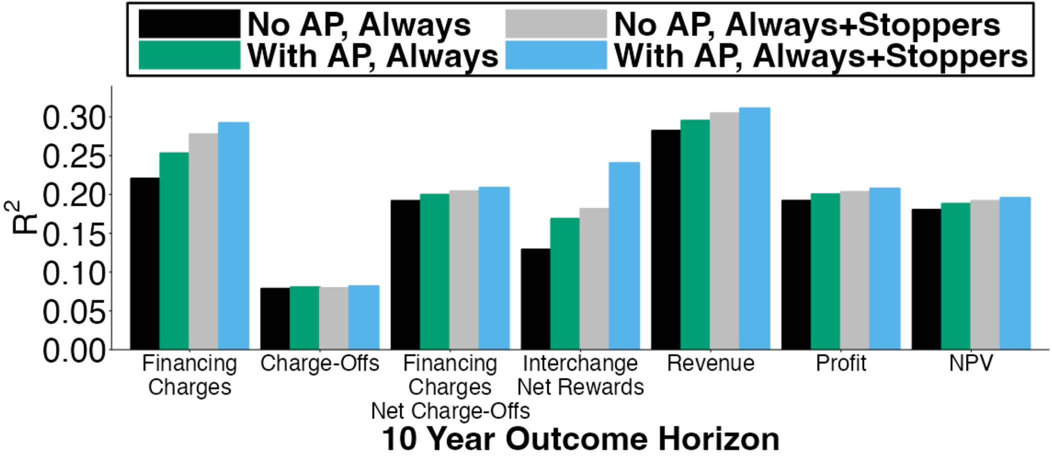
Predicting Financing Charges Net of Charge-Offs



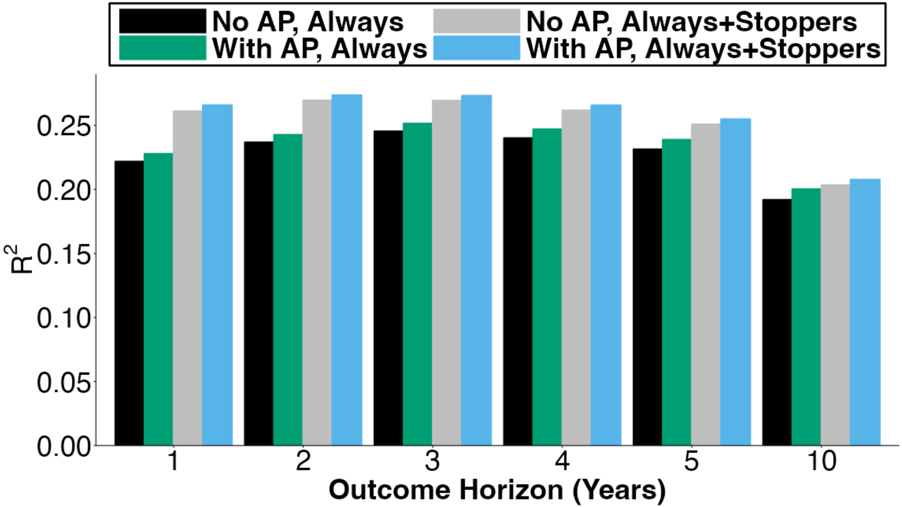
Predicting Financing Charges Net of Charge-Offs



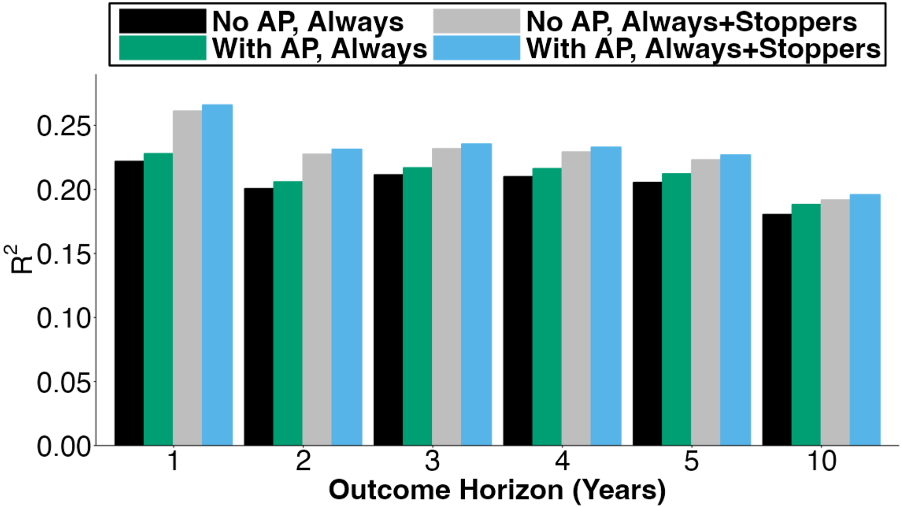
Predicting Lifetime Profits and its Components



Predicting Profits



Predicting NPV



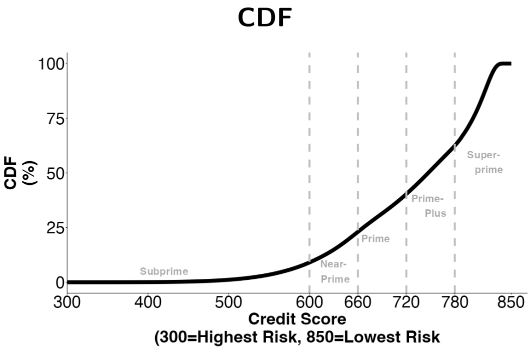
Predictive Results May Underestimate Importance of Interchange Revenue

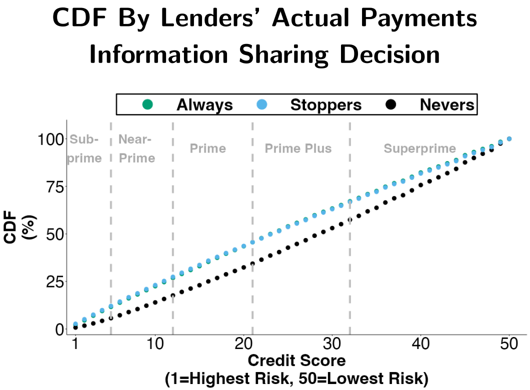
- Assume flat 0.5% margin of interchange net of rewards

- Interchange net of rewards may increase if lenders convert an account from a standard to a rewards card (which also generates annual fee revenue)

- Exclude lenders that **Never** share actual payments information

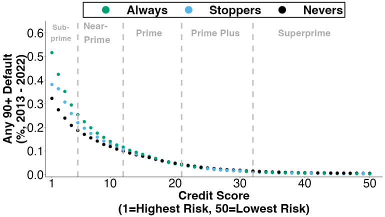
CDF of Credit Score



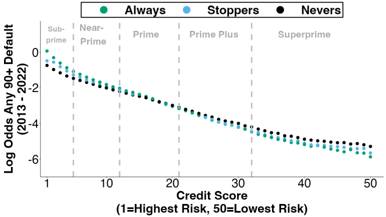


Credit Card Default Rates (2013–2022) Conditional on 2012 Credit Score

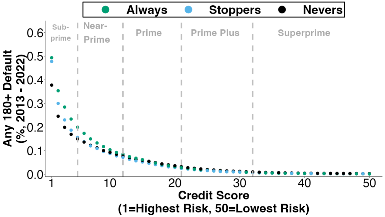
A. 90+ Days Past Due



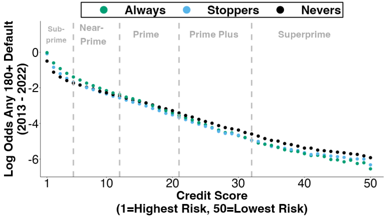
B. Log Odds 90+ Days Past Due



C. 180+ Days Past Due



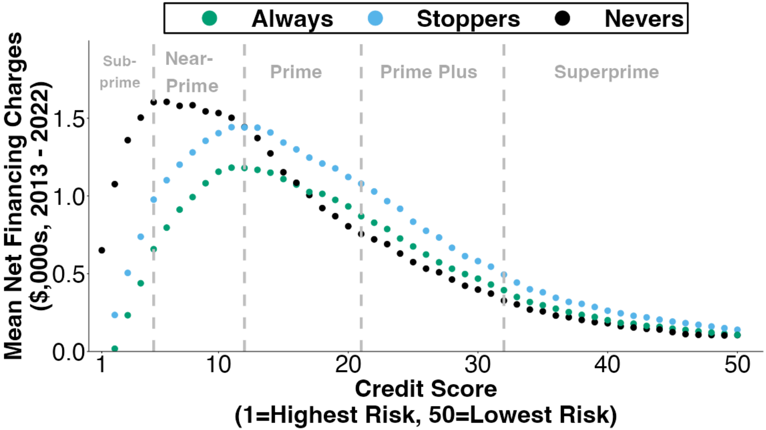
D. Log Odds 180+ Days Past Due



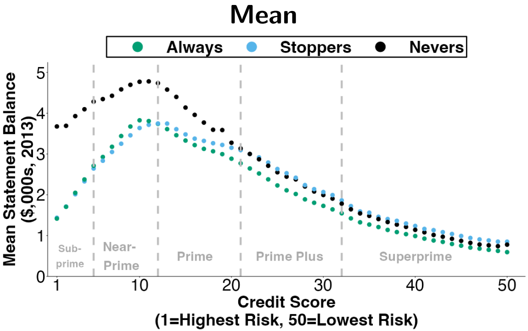
Selection in Sharing Actual Payments Data Residual of Credit Risk

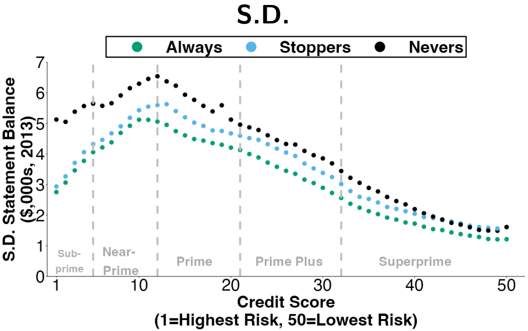
	Always	Stoppers	Nevers
Residual Tenure	71.0	97.6	136.5
(S.D.)	(73.8)	(75.5)	(106.0)
Residual Statement Balance	2,004.3	2,294.8	2,576.5
(S.D.)	(3,405.9)	(3,842.4)	(4,130.1)
Residual Proxy Spending	2,486.2	2,800.2	3,286.2
(S.D.)	(4,036.2)	(4,987.6)	(6,998.7)
Residual Financing Charges	130.1	235.0	156.5
(S.D.)	(351.3)	(534.5)	(440.8)
Residual Revolving Debt	1,538.1	1,707.6	N/A
(S.D.)	(3,047.7)	(3,413.6)	
Residual Spending	5,228.3	6,896.5	N/A
(S.D.)	(10,257.8)	(14,345.9)	

Financing Charges Net of Charge-Offs (2013 - 2022)

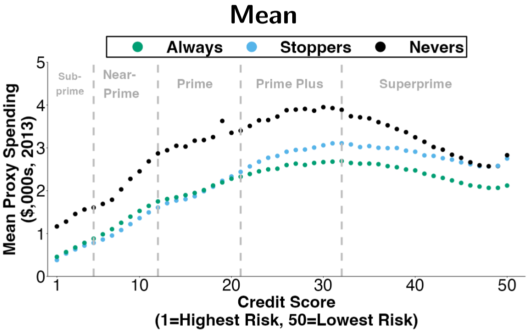


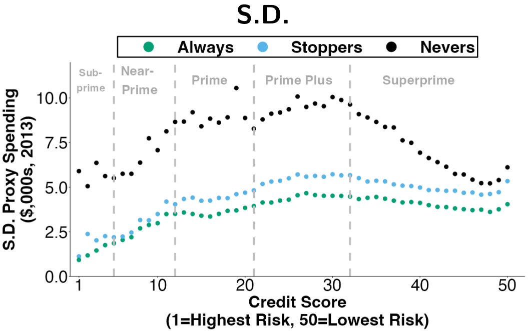
2013 Statement Balance



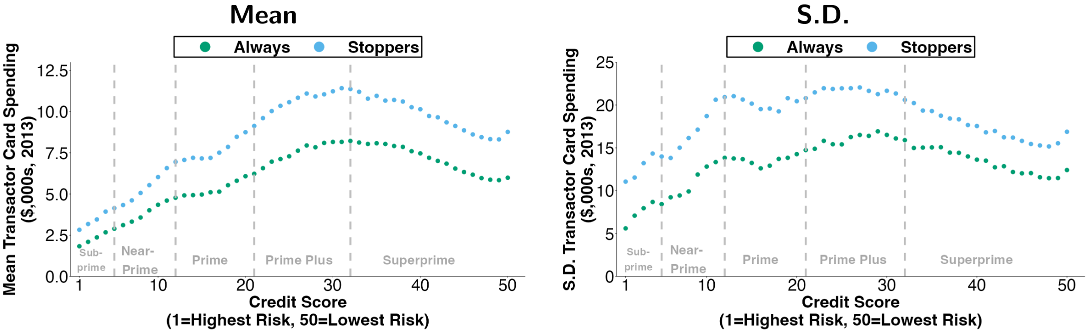


2013 Proxy Spending

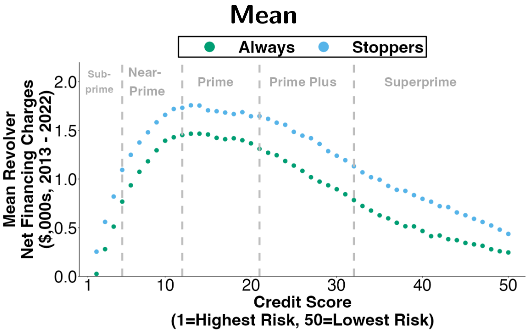


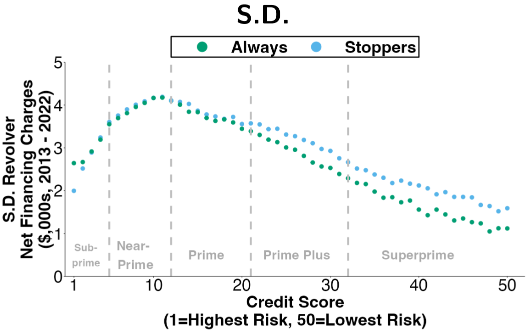


2013 Spending of 2012 Transactors



Financing Charges Net of Charge-Offs (2013 - 2022) of 2012 Revolvers

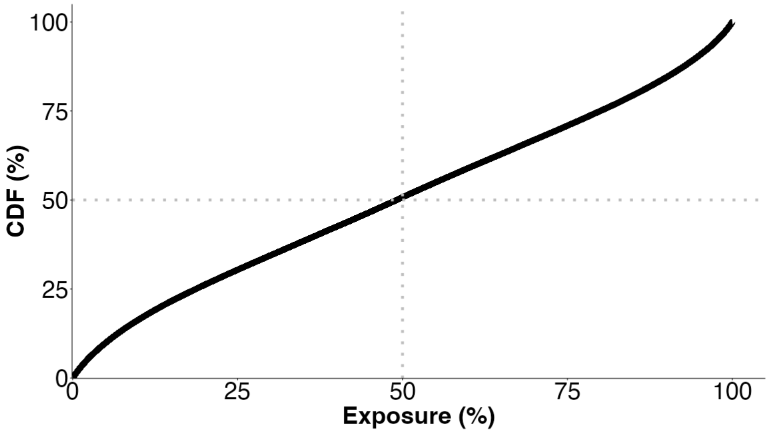




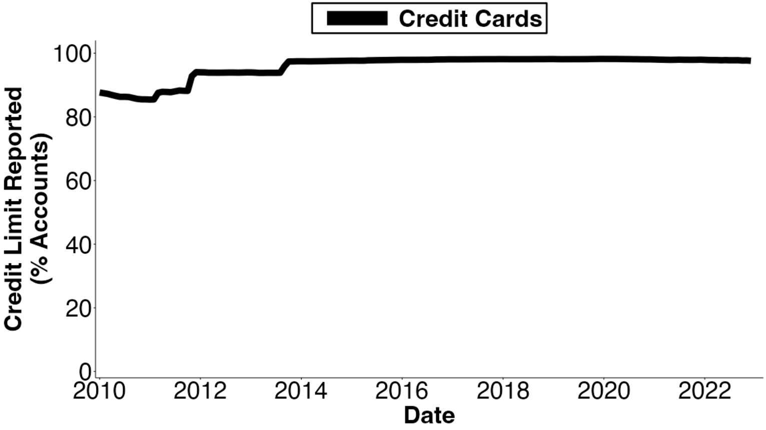
Selection in Sharing Actual Payments Data

	Always	Stoppers	Nevers
Credit Score	720.73	719.70	744.23
(S.D.)	(87.10)	(89.61)	(76.16)
Tenure	68.52	95.18	141.21
(S.D.)	(76.65)	(79.13)	(109.75)
Credit Limit	8,574.75	9,460.33	10,403.06
(S.D.)	(7,626.41)	(9,487.96)	(9,446.22)
Statement Balance	2,077.10	2,351.69	2,456.91
(S.D.)	(3,535.00)	(3,954.01)	(4,323.95)
Utilization	36.26	39.08	29.49
(S.D.)	(38.75)	(39.97)	(35.24)
Proxy Spending	2,454.67	2,752.78	3,369.77
(S.D.)	(4,059.19)	(5,044.94)	(7,917.64)

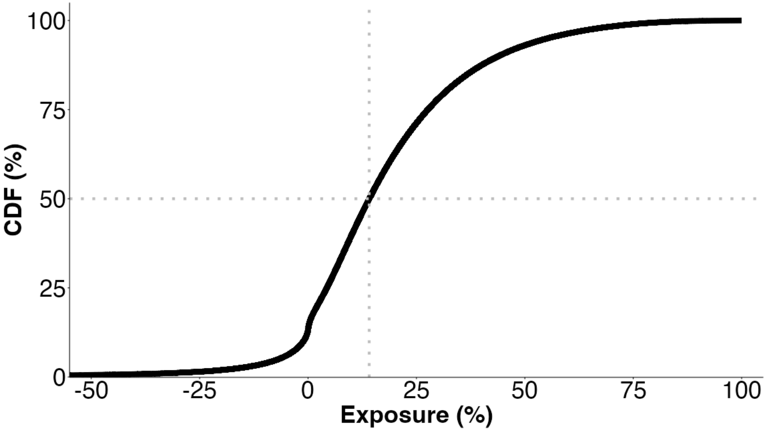
CDF of Trended Data Exposure Measure



Credit Limit Coverage



CDF of Credit Limit Exposure Measure



Mean 17%, Median 14%