PhD Dissertation Proposal

Benedict Guttman-Kenney (Chicago Booth)

27 September 2023

Thanks to NBER and Chicago Booth's Fama-Miller, Kilts, and Stigler Centers for supporting my research.

Essays in Household Finance (5 Years, 5 Papers)

 $See \ BGK_ResearchStatus.pdf \ and \ BGK_ResearchStatement.pdf \ on \ dropbox.$

Economics of Credit Information:

- Chapter 1. JMP
- Chapter 2. Disaster Flags
- Chapter 3. Credit Invisibles

Behavioral Household Finance:

- Chapter 4. Evaluating Hard Paternalism
- Chapter 5. Dynamic Heuristics

Post job market priority is getting chapter 3 to a working paper before graduation.

Chapters 4 and 5 are close to early working papers.

Other research expected to be published so excluded from dissertation.

Unraveling Information Sharing in Consumer Credit Markets

Benedict Guttman-Kenney (JMP)¹ & Andrés Shahidinejad²

¹Chicago Booth ²Northeastern University

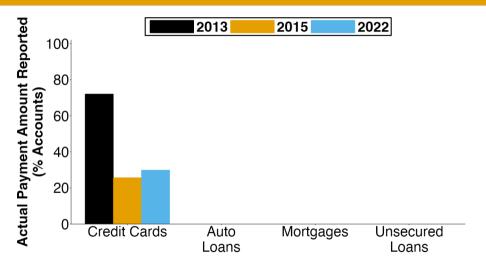
26 September 2023, Booth Finance Workshop

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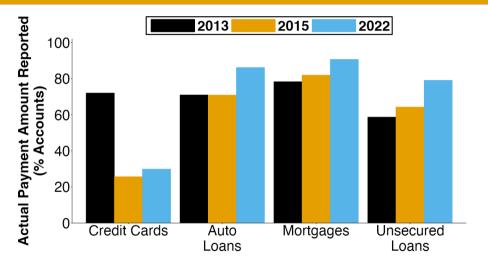
TransUnion (the data provider) has the right to review the research before dissemination to ensure it accurately describes TransUnion data, does not disclose confidential information, and does not contain material it deems to be misleading or false regarding TransUnion, TransUnion's partners, affiliates or customer base, or the consumer lending industry. Calculated (or derived) based on credit data provided by TransUnion through a relationship with the Kilts Center for Marketing at The University of Chicago Booth School of Business. No individual firms are identified in these data

Breakdown in information sharing

Breakdown in information sharing



Breakdown in information sharing in credit cards but not in other credit products



Empirical Methodologies:

- 1. Descriptive Evidence
- 2. Model and Predict Profitability
- 3. Three Difference-in-Differences Analyses

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- 3. Three Difference-in-Differences Analyses

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US consumer credit reporting data from TransUnion (Booth Kilts)

Learn about the limits of voluntary information sharing in developed markets.

What information is missing in YOUR credit report, why missing, its implications?

Four Parts to Paper

- 1. Unraveling Information Sharing
- 2. Consumer Credit Profitability
- 3. Credit Card Lender Selection
- 4. Competitive Effects

Part 1. Unraveling Information Sharing

- Describe unraveling
- Institutional details of data innovation ('Trended Data')
 - "The most important tool developed...since the credit score."
 - Data innovation harnesses actual payments for revealing profitable consumers to target marketing
 - Unraveling an unintended response to data innovation
- ullet Difference-in-differences: data innovation o information sharing
 - Credit cards as treatment group
 - Installment loans (auto loans, unsecured loans) as control group
 - ullet \downarrow 50 percentage point information sharing credit cards vs. installment loans
- Unraveling of market for sharing information

Part 2. Consumer Credit Profitability

- Framework for consumer credit profitability
- Measurement error by not observing actual payments data
 - 50% noise credit card spending
 - 5% noise revolving debt
- Predict profitability in credit cards, auto loans, unsecured loans
 - New methodology to estimate financing charges using institutional feature of credit card minimum payments
 - Data innovation ↑ predict profits
 - Data innovation ↑ interchange revenue (and also financing charges)

Part 3. Credit Card Lender Selection

- Only worst residual types remain sharing information (Akerlov-esque)
- Higher profitability and more dependence on interchange explains differential decisions
- Strategic foreclosure rather than co-ordination failure

Part 4. Competitive Effects

- ullet Difference-in-differences: data innovation o poaching
 - Heterogeneous exposure by % card balances with lenders sharing actual payment information.
 - $\bullet \ \, \mathsf{More} \ \mathsf{exposed} \, \to \, \mathsf{more} \ \mathsf{information} \ \mathsf{revealed} \, \to \, \uparrow \, \mathsf{credit} \ \mathsf{cards}.$
- Difference-in-differences: effects of mandating information sharing
 - Federal Trade Commission (FTC) mandating credit card limit reporting
 - Heterogeneous exposure by institutional feature of utilization.
 - Control of unaffected cards with same lenders.
 - ↑ 43 point credit score
 - ↑ credit access
 - ↑ competition:
 - Before information revelation, incumbent inside lender originates more
 - After information revelation, outside lenders expand credit

Contributions to Literature

- Household Finance: Importance of (i) credit card spending (ii) predicting lifetime profits. (e.g., Ausubel, 91; Agarwal, Comsisengphet, Mahoney, & Stroebel 15; Stango & Zinman, 16; Mukharlyamov & Sarin, 19; Nelson, 23; Agarwal, Presbitero, Silva, & Wiz, 23; Wang, 23)
- Financial Intermediation: Sensitivity of credit market to poaching.

 (e.g., Diamond, 84; Ramakrishan & Thakor, 84; Pagano & Japelli, 93; Bouckaert & Degryse, 06; Huang, He, Zhou, 23; Blattner, Hartwig & Nelson, 23; Jansen, Nagel, Yannelis, Zhang, 23)
- Information Economics: Document information sharing breakdown in developed market. (e.g., Akerlof, 70; Rothschild & Stiglitz, 76; Roth & Xing, 94)
- Methodological: New methodology for estimating credit card financing charges.
 (e.g., Ganong & Noel, 20; Gross, Notowidigdo, Wang, 20; Shahidinejad, 23; Yannelis & Zhang, 23)

Roadmap

- 1. Unraveling Information Sharing
- 2. Consumer Credit Profitability
- 3. Credit Card Lender Selection
- 4. Competitive Effects

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- 2. Importance of predicting lifetime profits and spending to credit card business
 - Observing payments crucial to identifying spending driving interchange revenue.

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 - High spenders are often longer tenure & profitable.
- 3. Mandating information sharing can ↑ competition and ↑ credit access

1. Unraveling Information Sharing

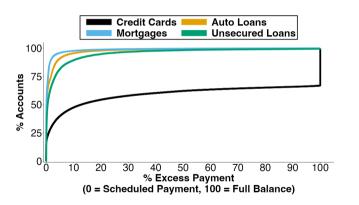
Data: University of Chicago Booth's TransUnion Consumer Credit Panel (BTCCP)

- BTCCP is TransUnion anonymized sample of US credit reporting data.
- Sample of 1 in 10 consumers with US credit reports.
- Monthly, individual credit tradelines + consumer-level data (e.g. credit scores).
- Anonymized consumer, trade, and furnisher identifiers.
- Apply standard data cleaning steps
 (Gibbs, Guttman-Kenney, Lee, Nelson, van der Klauuw, Wang, AEA 2023 Panel)
- Lender heterogeneity studying 84 credit card furnishers (92-93%), of which 6 (66-67%).

No individual firms are identified in BTCCP data.

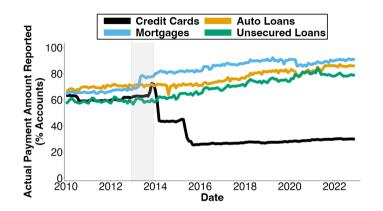
What Are Actual Payment (Amounts) Data?

Actual Payment Amounts	Scheduled Payment Amounts
How much paid	Minimum payment due



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

Breakdown in sharing credit card actual payments with US credit bureau



Also occurs in other US credit bureaus (Equifax & Experian).

No credit card lenders plan to to voluntarily restart reporting actual payments (CFPB).

Policy relevant



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

By John McNamara - MAY 25, 2022

CFPB documents:

- Non-Reporters: American Express, JPMorgan Chase, Citibank, Bank of America, Capital One, Discover.
- Of these:
 - 2 never report
 - 1 stopped in 2014
 - 3 later stopped (1x 2014, 2x 2015)

Some numbers

- Only 24% of credit cardholders have no missing data.
- 165 m consumers missing information.
- None of six largest credit card lenders report (2/3 market share)

Why is YOUR credit card lender not reporting information in YOUR credit report?

When your auto loan, mortgage, unsecured loan are!

Data Innovation

Trade-offs of information sharing

Lenders Trade-Offs

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

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Trade-Offs for Credit Reporting Agencies:

- Use technology to produce data products to sell to lenders.
- S.t. incentive compatible for lenders to share information.

Institutional details on credit reporting data

Sharing information with US credit reporting agency is:

- Voluntary
- Non-Reciprocal

If share information, law (FACT Act, FCRA) requires:

- Loan Terms: origination amount, # payments, scheduled payment, open and close dates.
- Loan Performance: balance, delinquency status, and (post-2010) credit limit.

Actual payments data not required by law.

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US credit reporting data used by lenders for:

- Credit risk (underwriting, portfolio management).
- Marketing (pre-selected credit offers)

Credit Bureaus Launched Data Innovation 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 is the most important tool developed by the credit reporting agencies since the advent of the credit score." – Director of Credit Card Risk, 2014

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

"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.

Reveals heterogeneous credit cards behaviors driving profitability.

Use for targeted marketing & credit risk.

"Trended Data" is technological advance \(\ \) information from data

- New information revealed from data
- **Cost reduction:** Technically lenders could construct from raw data themselves. In practice they did not. Why?
 - Technological constraints:

"It took us time just to build the infrastructure to house the data." (Equifax 2013)

- Legal constraints:

compliance concerns prevented lenders constructing trended data.

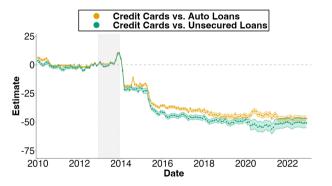
- Cost constraints:

constructing trended data would mean purchasing 24 archives.

Difference-in-Differences Effect of Trended Data on Reporting

Credit cards more exposed as use for pre-selected marketing

 \downarrow 47.1 to 51.0 p.p. in reporting credit cards vs. auto loans / unsecured loans



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Unraveling of actual payments data is US-specific

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

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Why?

- **UK** Principles of Reciprocity by industry body Steering Committee on Reciprocity:
 - (i) bans use of credit files for pre-selected marketing to individuals
 - (ii) reciprocality in sharing data

Unraveling of actual payments data is US-specific

Actual payments data remain reported 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 files for pre-selected marketing to individuals
 - (ii) reciprocality in sharing data
- Canada has limited use of credit files for marketing e.g. can use for geographic variables but not for individual targeting.

Much less trade-off of sharing actual payments data in UK or Canada: less risk of poaching.

2. Consumer Credit Profitability

Consumer Credit Profitability Relies on Predicting Consumer Behaviors

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

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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t = 2:

• \$250 payment amount

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t = 2:

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- \$12 interest + \$30 fee = \$42 financing charges

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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
- \$2,000 new spending (→ generates \$10 net interchange revenue)
- \$2,792 statement balance & \$70 minimum payment due

```
t = 1:
```

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t = 2:

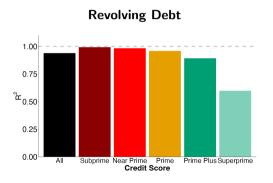
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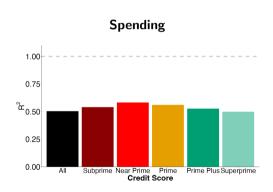
```
spending_t = statement \ balance_t - statement \ balance_{t-1} + payment_t - fincharge_t revolving \ debt_t = statement \ balance_{t-1} - payment_t
```

If $payment_t$ unobserved, \uparrow noise to measurement of spending & revolving debt

OLS regressions using Dec 2013 with statement balance.

Out-of-sample R^2 shown.

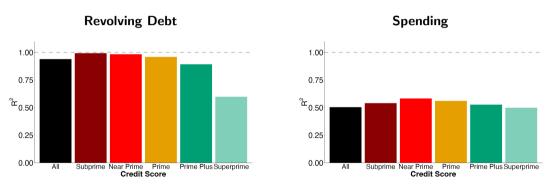




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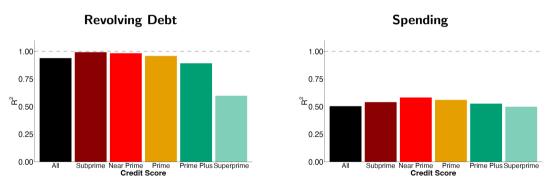


Noise impedes targeting of pre-selected credit card offers.

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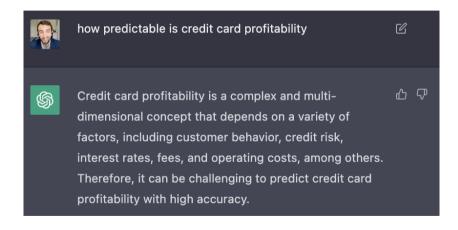
Out-of-sample R^2 shown.



Noise impedes targeting of pre-selected credit card offers.

Bad news for academics & policymakers measuring revolving debt or consumption.

Predicting Credit Card Profitability is Hard!



How Predictable are Consumer Behavior & Profitability?

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

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

$$\Pi_{PRE}^{INST} = E_{t=0}[\Pi_{POST}^{INST}|X_0] = \sum_{t=1}^{T} \delta^t \Big(r_t - E_{t=0}[q_t|X_0]\Big) + E_{t=0}\Big[\sum_{t=1}^{T} \delta^t \Big(f_t - c_t\Big)|X_0\Big] - a^{t=0}$$

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Estimate Profitability and its Components in Data:

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

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Estimate Profitability and its Components 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.

Lender's problem is predicting profitable types to target marketing

1. **No actual payments data.** Use interactions of credit score, credit limit, statement balances, utilization, delinquency etc

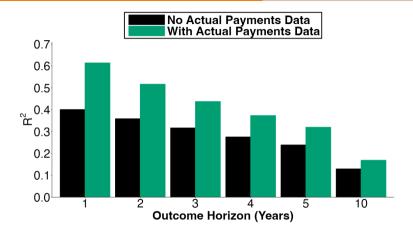
$$Y_{i,2022} = X'_{i,2012}\beta + \varepsilon_{i,2022} \tag{1}$$

2. With Actual Payments Data: Model 1 + interactions of actual payments data with Model 1 variables.

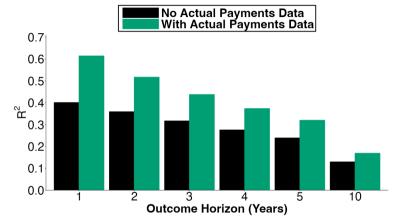
$$Y_{i,2022} = X'_{i,2012}\beta + Z'_{i,2012}\lambda + \varepsilon_{i,2022}$$
 (2)

Use data to December 2012 to predict 2013+ outcomes. Show out-of-sample R^2 .

Actual Payments Data Predicts Interchange



Actual Payments Data Predicts Interchange



1 year

 R^2 : 0.4006 \rightarrow 0.6139,

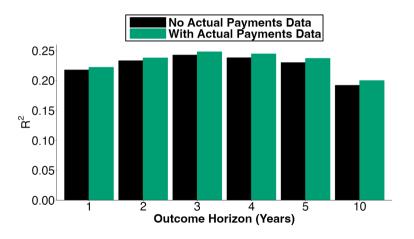
Portfolio value: +24%

10 year

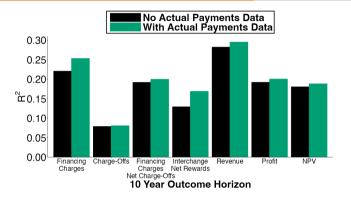
 R^2 : 0.1291 \rightarrow 0.1687,

Portfolio value: +13%

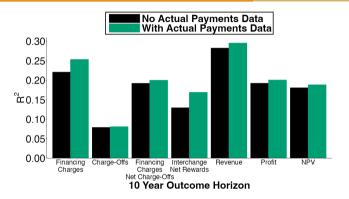
Actual Payments Data Predicts Profitability: Small Uplift for Financing Changes Net Charge-Offs



Actual Payments Data Predicts Profitability: Especially Spending Driving Interchange Revenue



Actual Payments Data Predicts Profitability: Especially Spending Driving Interchange Revenue



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

3.Credit Card Lender Selection

Unraveling Driven By Some Credit Card Lenders Stopping Reporting

Aggregate 84 furnishers in BTCCP based on 2012 vs. 2015 reporting:

Group	% 2012 Cards	% 2012 Balances
Always: Share AP data in 2012 & 2015.	18%	17%
Stoppers: Share AP data in 2012 but not 2015	47%	47%
Nevers: Never share AP data in 2012 & 2015	32%	35%
Others: Everyone else.	3%	1%

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Lenders' Responses to CFPB:

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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Stoppers:

- Firm 4: "Doesn't believe benefits outweigh proprietary interests."
- 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."

Noise heterogeneously affects credit card lenders' business models

Firms 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 firms.

Selection in Reporting 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	8,575.06	9,461.19	10,409.80
(S.D.)	(7,631.69)	(9,500.02)	(9,542.53)
Statement Balance	2,191.83	2,417.90	2,571.61
(S.D.)	(3,795.31)	(4,263.29)	(4,873.83)
Utilization	0.36	0.39	0.29
(S.D.)	(0.39)	(0.40)	(0.35)
Proxy Spending	2,454.94	2,754.02	3,385.40
(S.D.)	4,072.05	5,100.28	7,465.29

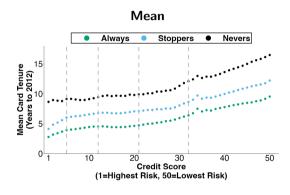
Adverse Selection in Reporting Actual Payments Data Residual of Credit Risk: Always < Stoppers < Nevers

	Always	Stoppers	Nevers
Residual Tenure	-34.78	-8.19	30.68
(S.D.)	(73.80)	(75.50)	(105.98)
Residual Credit Limit	-713.94	177.91	147.72
(S.D.)	(6,693.71)	(8,497.69)	(9,337.62)
Residual Statement Balance	-319.20	-75.50	282.11
(S.D.)	(3,635.34)	(4,129.43)	(4,655.80)
Residual Proxy Spending	-425.54	-110.51	389.84
(S.D.)	4,049.22	5,043.53	7,446.02

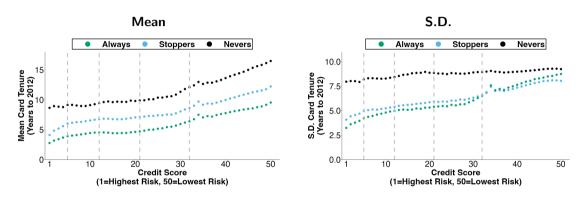
Residual of 100 credit score quantiles.

Credit risk not main reason for differential reporting

Lenders Have Different Card Tenure for Given Risk: Informational Rents!



Lenders Have Different Card Tenure for Given Risk: Informational Rents!



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

Develop New Methodology for Measuring Financing Charges

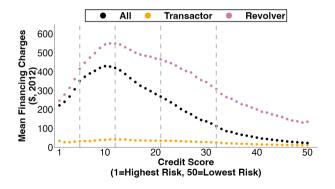
Minimum payment (M_t) determined by: $M_t = \max\{\$\mu, \ \theta\% \ b_t + r_t + f_t\}$

- ullet Infer μ and $\theta\%$ for each furnisher using observed minimum payment and statement balance
- Observed minimum payment predicted minimum payment = financing charges.

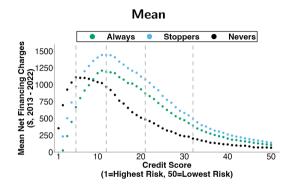
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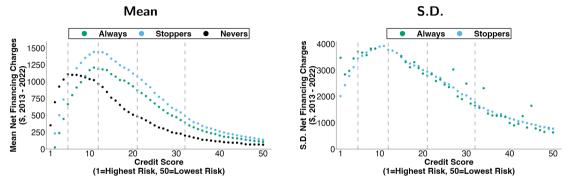
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Always & Stoppers: Financing Charges - Charge-Offs (2013 to 2022)



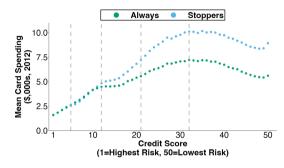
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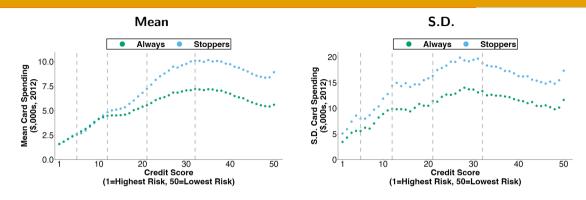
- Revolving larger balances, similar revolving rate:
- Mean (S.D.) Revolving Debt: Stoppers \$1,705 (\$3,597) vs . Always \$1,548 (\$3,201)
- Means Any (Majority) Transacting: Stoppers 71.0% (51.3%) vs . Always 77.4% (51.2%)

Always & Stoppers: Spending (2012 to 2013)

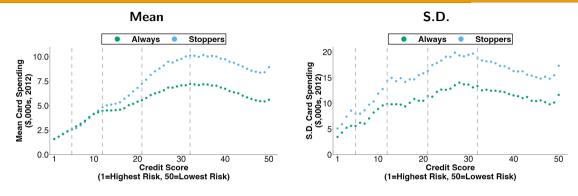




Always & Stoppers: Spending (2012 to 2013)



Always & Stoppers: Spending (2012 to 2013)



- 2012 Mean (S.D.) Spending: Stoppers \$7,143 (\$15,504) vs . Always \$5,380 (\$10,729)
- Comparing to Fed aggregate credit card spending data indicates Nevers > Stoppers.
- Variation within-consumer's card wallet.
 - High returns from being 'top-of-wallet'.

Are transactors profitable?

• Hard to reconcile with large, costly marketing to superprime transactors.

Credit Card Offers Mainly Superprime

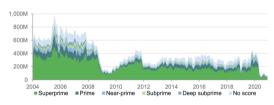


Source: CFPB, 2021

Are transactors profitable?

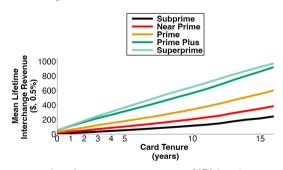
• Hard to reconcile with large, costly marketing to superprime transactors.

Credit Card Offers Mainly Superprime



Source: CFPB, 2021

Lifetime Interchange Revenue By Card Tenure & Credit Score



Average transactor may have 'low' p.a. net revenues...but longer tenure means NPV>0.

For Always, interchange increases mean lifetime profits of 2012 transactors: \$230 to \$450.

Recap of key findings so far

- Credit card profitability depends on ex-post consumer behaviors with multiple dimensions of information asymmetry & revenue streams.
- Observing actual payments data crucial to measuring consumer behaviors.
- Unraveling of reporting actual payments data by credit card lenders (2013 2015).
- Timing due to credit bureau data innovation revealing private consumer behaviors:
 - spending (driving interchange revenue)
 - revolving (driving interest revenue).
- Adverse selection in reporting.
 - Longer tenure.
 - Higher mean and variance.

4. Competitive Effects

Difference-in-Differences: Effects of Data Innovation on Credit Card Poaching

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

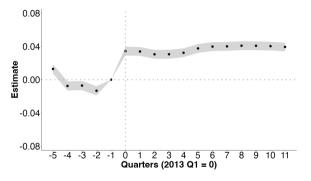


$$EXPT_i \equiv rac{\sum_c 1\{F_c \in \mathbf{Sharers}\} \times b_{i,c}}{\sum_c b_{i,c}}$$

Balanced panel of consumers 2011 to 2015.

Data Innovation Caused ↑ **Poaching**

Outcome: Any New Credit Card Opened



$$Y_{i,t} = \sum_{ au
eq -1} \delta_{ au} \Big(D_{ au} imes extit{EXPT}_i \Big) + \gamma_i + \gamma_t + arepsilon_{i,t}$$

Mandating Information Sharing

Effects of Mandating Information Sharing

Policy

- 1990s most credit limits not reported
 - ightarrow Regulatory pressure and threats by agencies to restrict access
- 2000s most but not all lenders reporting credit limits (Hunt, 05)
 - → Federal Trade Commission (FTC) rules requiring reporting credit limits from July 2010.
- By 2010s full coverage.

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How credit limits matter

- 20% to 30% of your credit score is credit utilization: balance credit limit
- If no credit limit reported: use highest historical account balance.
 - \rightarrow Typically overstates utilization.
 - \rightarrow Consumers appear riskier to outside lenders.



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

Study furnishers revealing credit limits 20.9 million accounts in November 2011

Exposure measure: Difference in utilization rate from credit limit revelation.

$$\textit{EXPL}_i = \Big(\frac{\sum_{c} b_{i,c,t-1}}{\sum_{c} l_{i,c,t}} - \frac{\sum_{c} b_{i,c,t-1}}{\sum_{c} \mathbf{1}\{l_{i,c,t-1} = \textit{null}\}h_{i,c,t-1} + \sum_{c} l_{i,c,t}}\Big) \times -1$$

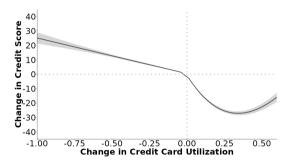
Difference-in-Differences: Control group is consumers holding cards with same furnisher but where limits reported pre November 2011.

$$Y_{i,t} = \sum_{\tau \neq \mathsf{Nov} \ 2009} \delta_{\tau} \Big(D_{\tau} \times \mathsf{EXPL}_i \Big) + \gamma_i + \gamma_t + \varepsilon_{i,t}$$

49 month balanced panel of consumers who held card with furnisher (at least) 2009 - 2011.

Information Revelation † Credit Scores

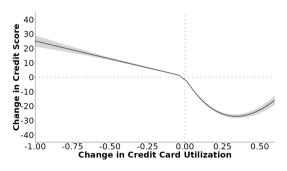
Non-Parametric Relationship



Consumers with information revealed.

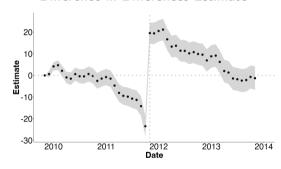
Information Revelation ↑ Credit Scores

Non-Parametric Relationship



Consumers with information revealed.

Difference-in-Differences Estimate



Consumers appeared riskier before revelation!

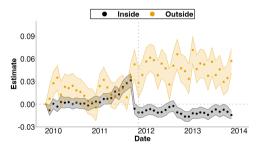
Information Revelation ↑ Competition & Credit Access

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

Information Revelation ↑ Competition & Credit Access

Outcomes by inside and outside lenders.

Any New Credit Cards Opened

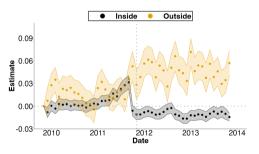


- Insider lender originating pre-revelation.
 - Outsiders poach post-revelation.

Information Revelation ↑ Competition & Credit Access

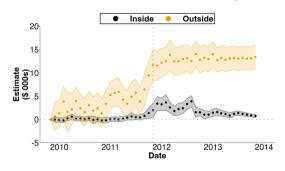
Outcomes by **inside** and **outside** lenders.

Any New Credit Cards Opened



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Credit Limits of New Credit Card Opened



- Outsiders more credit post-revelation.

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 - Observing payments crucial to identifying spending driving interchange revenue.
 - High spenders are often longer tenure & profitable.
- 3. Mandating information sharing can \uparrow competition and \uparrow credit access

PhD Dissertation Proposal

Benedict Guttman-Kenney (Chicago Booth)

27 September 2023

Thanks to NBER and Chicago Booth's Fama-Miller, Kilts, and Stigler Centers for supporting my research.

Essays in Household Finance (5 Years, 5 Papers)

 $See \ BGK_ResearchStatus.pdf \ and \ BGK_ResearchStatement.pdf \ on \ dropbox.$

Economics of Credit Information:

- Chapter 1. JMP
- Chapter 2. Disaster Flags
- Chapter 3. Credit Invisibles

Behavioral Household Finance:

- Chapter 4. Evaluating Hard Paternalism
- Chapter 5. Dynamic Heuristics

Post job market priority is getting chapter 3 to a working paper before graduation.

Chapters 4 and 5 are close to early working papers.

Other research expected to be published so excluded from dissertation.

2. Disaster Flags: Credit Reporting Relief from Natural Disasters

What paper does:

- Five facts
- Effects on credit scores and credit access
- Counterfactual from automatically masking disaster defaults

Status:

- In May, presented at Philly Fed and discussed with senior CFPB policymakers.
- Presenting at APPAM in October.
- Submitted to NBER Household Finance and RAND conferences.
- Aim to submit paper in 2024.

3. Credit Invisibles With Tony Cookson and Will Mullins

- Preparing input file for TransUnion.
- Examine consumers of same age with different years of credit visibility based on year of SSN assignment (Bernstein et al. 22).
- Effects on time to becoming credit visible and credit access
- Need working paper before graduate!

Potential Project on Auto Loan Prepayment?

Scoping paper with Andres with TU data

Aim: Write THE definitive paper on this topic.

Auto loan prepayment barely studied in literature. Literature focuses on mortgage prepayment.

- Describe auto loan prepayment over 20+ years.
- When do consumers prepay auto loans? What happens to other credit when they do?
- Difference-in-Differences effect of auto loan prepayment bans on auto loan market.

CFPB collecting new administrative auto loan data and may be able to collaborate in future.

Behavioral Household Finance: 2 Projects

4. Evaluating Hard Paternalism: With Jason Allen and Michael Boutros

- Effects of *uparrow* minimum payments on new and existing credit cards in Quebec.
- Old cards ↓ debt. New cards ↑ debt as lenders ↑ credit limits but maybe some ↓ access.
- Next Steps: Presenting at IPA in October. Write up draft.
- Longer-term aim: Inform optimal minimum payment policy (run survey and link to admin data?) with Jason and Michael's structural expertise!

4. Dynamic Heuristics

- ullet Elasticity of round number expenditure (e.g., PQ = £20.00) heuristics to prices .
- Common heuristic, elastic, when gas (petrol) P \uparrow , use heuristc \downarrow and rounders \uparrow visits.
- Post-Job Market: Use NBER research funds to run survey and write-up working paper.

Thank you!



☑ benedict@chicagobooth.edu

