Who Pays for Your Rewards? Cross-Subsidization in the Credit Card Market

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August 25, 2022
EEA-ESEM Congress 2022
Bocconi University, Milan

Motivation

- Unsophisticated consumers often make costly "mistakes" when using financial products
  - Over-indebtedness (Meier and Sprenger, 2010; Gathergood, 2012)
  - High overdraft fees (Stango and Zinman, 2014)
  - Suboptimal repayment behavior (Kuchler and Pagel, 2021)

- Banks can design financial products to exploit these mistakes
  - Salient, front-loaded benefits combined with shrouded, back-loaded costs (DellaVigna and Malmendier, 2004; Heidhues and Kőszegi, 2010, 2017)

⇒ **Cross-subsidy from naive to sophisticated consumers**
  - "Naive consumers who do not recognize their self-control problems cross-subsidize sophisticated consumers." (Gabaix and Laibson, 2006)

Research Questions

- Empirical studying such cross-subsidization is difficult, because:
  - financial decision-making depends on hard-to-measure variables
  - it requires individual-level data on the costs and benefits of financial product usage
- We use credit card reward programs as an ideal laboratory to:
  - test whether there is cross-subsidization from naïve to sophisticated consumers in financial product markets
  - quantify such cross-subsidization
  - study who benefits and who pays for it

Literature Contribution

A Primer on Credit Card Reward Programs

- Reward programs offer benefits to cardholders per dollar spent on the credit card (cash back, miles, points)
- As of 2019:
  - 75% of consumers use credit cards
  - reward cards account for 80% (60%) of total credit card spending (new card originations)
  - the largest U.S. banks paid out **$35 billion in rewards**
- While consumers pay for the use of credit cards through interest payments and fees, they can also earn money through rewards

⇒ These costs and benefits are likely not equally distributed across cardholders

Data

- Data source: Federal Reserve Board's Y-14M data (BHCs with >$100 billion total assets)
- Covers 70% of aggregate outstanding balances on consumer credit cards (CFPB, 2019)
- Monthly account-level data on:
  - Accumulated rewards, interest and fee payments, spending and outstanding balances, credit limits, FICO scores, borrower income, borrower ZIP codes, and much more.
- Cross-section of 166.2 million cards as of March 2019

Estimating Net Rewards

FICO Scores and Financial Sophistication

- FICO scores are designed to capture borrowers' creditworthiness and measure their likelihood to repay debt on time.
- FICO scores are largely based on:
  - Borrower's payment history
  - Outstanding debt relative to available credit

⇒ FICO scores capture the same type of credit card behavior that is associated with a lack of financial sophistication (Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2015):

  - Over-indebtedness
  - Higher fee payments
  - Suboptimal repayment behavior

⇒ We use FICO scores as a proxy measure of financial sophistication.

FICO Scores as Proxy Measure

Methodology

- Definition of net rewards

$$\text{Net Rewards}_{i,t} = \text{Gross Rewards}_{i,t} - \text{Interest Paid}_{i,t} - \text{Total Fees}_{i,t}$$

- Regression specification

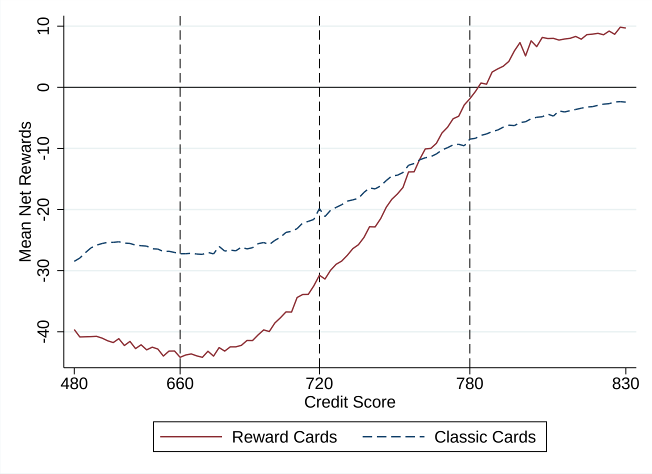
$$\mathrm{Y}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F\right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

where

  - *Reward Card* = 1 if card offers rewards; and 0 otherwise.
  - D^F = FICO bucket dummy variable (<660 = Sub-prime; 660-720 = Near-prime; 720-780 = Prime; >780 = Super-prime)
  - $\alpha_{f,w,z,b} = \text{FICO}_{Q100} \times \text{Income}_{Q100} \times$ ZIP Code $\times$ Bank FE
  - X_i^m = Card-level control variables (credit limit, age of card, promotion dummy, joint account dummy)
  - X_j^n = Borrower-level control variables (bank relationship dummy, ongoing bankruptcy dummy)

Borrower Fixed Effects | Descriptive Statistics

Net Rewards Across the FICO Distribution



⇒ Aggregate annualized cross-subsidy of \$15.5 billion.

Regression Analysis: Net Rewards

$$Y_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F\right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

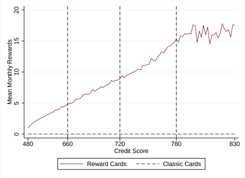
	Net Rewards			
	(1)	(2)	(3)	(4)
Reward Card	6.80***	6.11***	5.11***	
	(0.40)	(0.51)	(0.49)	
Reward Card × Sub-Prime				−5.07***
				(0.57)
Reward Card × Near-Prime				−5.14***
				(0.77)
Reward Card × Prime				11.67***
				(0.60)
Reward Card × Super-Prime				21.42***
				(0.96)
Card Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
FE: Bank × ZIP × Income	Y	N	-	-
FE: Bank × ZIP × FICO	N	Y	-	-
FE: Bank × ZIP × Income × FICO	N	N	Y	Y
Observations	166,205,496	166,205,496	166,205,496	166,205,496
Mean Y	-15.09			

Robustness: Borrower FE   Aggregate Net Rewards

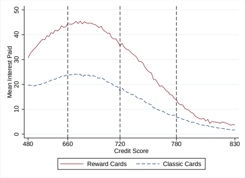
Net Reward Components Across the FICO Distribution

$$\text{Net Rewards}_{i,t} = \text{Gross Rewards}_{i,t} - \text{Interest Paid}_{i,t} - \text{Total Fees}_{i,t}$$

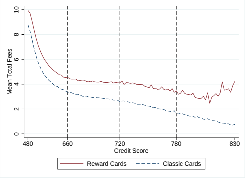
(a) Gross Rewards



(b) Interest Paid



(c) Total Fees



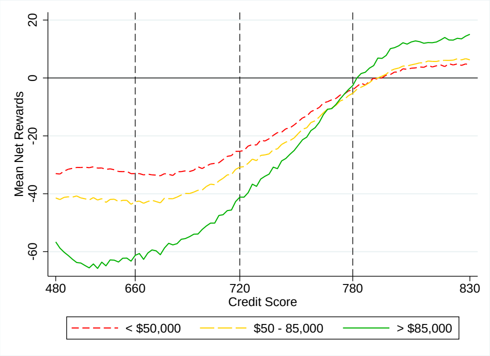
⇒ Sophisticated consumers earn more rewards, pay less interest charges, pay less fee charges.

⇒ In the paper, we show: This is driven by higher spending alongside lower borrowing of high FICO borrowers.

Regression Analysis Credit Card Usage

Net Rewards of Reward Cards by Income Group

- What about income?
- Note: FICO scores and income are not strongly correlated (Beer, Ionescu, and Li, 2018)



⇒ Sophisticated high-income consumers benefit at the expense of naive high-income consumers.

Regression Analysis

The Bank's Perspective

- So far: Borrower perspective
- Now: Bank perspective: Pricing and profits
  - Do banks lure people into reward cards?
  - How do banks profit across the FICO distribution?
- Recall: Definition of net rewards (borrower perspective)

$$\text{Net Rewards}_i = \text{Gross Rewards}_i - \text{Interest Paid}_i - \text{Total Fees}_i$$

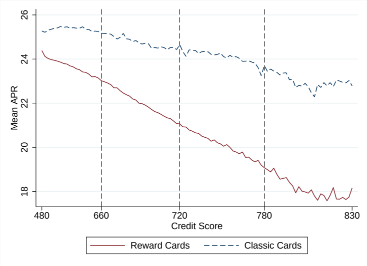
- Definition of profits (bank perspective)

$$\begin{aligned}\text{Profit}_i = {} & \text{Interest Paid}_i + \text{Total Fees}_i + \text{Interchange Income}_i \\ & - \text{Gross Rewards}_i - \text{Realized Charge-Offs}_i\end{aligned}$$

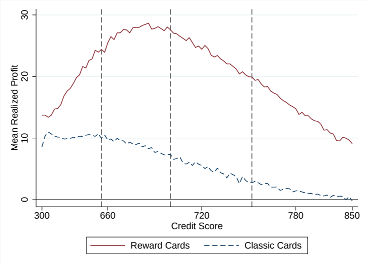
- Interchange Income = 2%×Purchase Volume (Agarwal et al., 2015)
- Realized Charge-Offs = Charge-off if account is 180 days delinquent

The Bank's Perspective: Pricing and Profits

(a) APRs



(b) Bank Profits

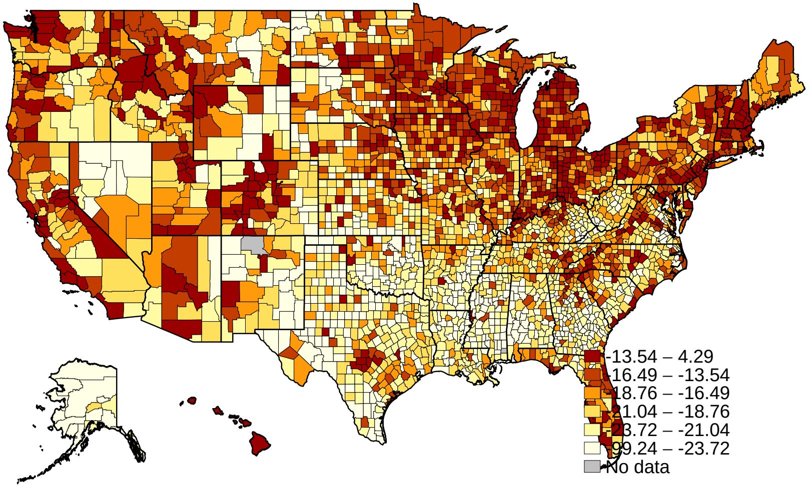


$\Rightarrow$ Banks lure consumers into the use of reward cards.

$\Rightarrow$ Banks profits are highest in the middle of the FICO distribution.

Regression Analysis Revenue Shares

The Geography of Net Rewards



Regression Analysis: The Geography of Net Rewards

$$\text{Net Reward}_{i,z} = X_k + \varepsilon_{i,z}$$

	Net Rewards			
	(1)	(2)	(3)	(4)
Low Education	-0.39^{***}			
	(0.04)			
Household Income (in \$k)		0.12^{***}		
		(0.01)		
Population Density			0.10^{***}	
			(0.04)	
Black Population Share				-0.16^{***}
				(0.01)
Observations	166,205,496	166,205,496	166,205,496	166,205,496
Adjusted R^2	0.39	0.01	0.35	0.19

Conclusion

- Sophisticated consumers profit from reward cards, while naive consumers lose money both in absolute terms and relative to classic cards.
- Results not driven by income: Sophisticated, high-income consumers benefit the most, but naive high-income consumers pay the most.
- Banks lure consumers into using reward cards by offering lower APRs.
- Reward cards transfer wealth from from less to more educated, from poorer to richer, from rural to urban, and from high to low minority areas.

APPENDIX

Literature Contribution

- Cross-subsidy from naive to sophisticated consumers in retail financial markets
  - Theoretical: DellaVigna and Malmendier (2004); Gabaix and Laibson (2006); Heidhues and Kőszegi (2010, 2017)
  - Empirical: Guiso, Pozzi, Tsoy, Gambacorta, and Mistrullie (2021); Fisher, Gavazza, Liu, Ramadorai, and Tripathy (2021)
    - Empirical evidence on cross-subsidization in mortgage markets.
  - Our paper: Evidence on cross-subsidization in credit card markets.
- Credit card rewards
  - Hayashi (2009); Schuh, Shy, and Stavins (2010); Felt, Hayashi, Stavins, and Welte (2020)
    - Focus on cross-subsidy from cash users to credit card users.
  - Our paper: Focus on cross-subsidy within credit card users.

Back

Estimating Monthly Net Rewards

- Definition of net rewards

$$\text{Net Rewards}_{i,t} = \text{Gross Rewards}_{i,t} - \text{Interest Paid}_{i,t} - \text{Total Fees}_{i,t}$$

- Note: Variable *Gross Rewards* not contained in the dataset
- But: We do observe *Cumulative Rewards* each month

$$\text{Cumulative Rewards}_{i,t} = \text{Cumulative Rewards}_{i,t-1} + \text{Gross Rewards}_{i,t} - \text{Redemptions}_{i,t}$$

$\Rightarrow$ Goal: Estimate *Gross Rewards* from data

Back

Estimating Monthly Net Rewards

- **Estimation Step 1:** Calculate effective reward rate of card i

$$\text{Card-Specific Reward Rate}_{i,t} = \frac{\Delta\text{Cumulative Rewards}_{i,t}}{\text{Purchase Volume}_{i,t}}$$

- Note: This reward rate is correct if *Redemptions* are zero
- **Estimation Step 2:** Cluster credit cards at the individual product level k by:
  - Bank × Credit card type × Product type × Card network × Reward type × Fee type × Fee level

$$\text{Estimated Reward Rate}_{i,t} = Q^{k}_{50}\left(\text{Card-Specific Reward Rate}_{i \in k,t}\right)$$

- **Estimation Step 3:** Calculate *Gross Rewards*

$$\text{Gross Rewards}_{i,t} = \text{Estimated Reward Rate}_{i,t} \times \text{Purchase Volume}_{i,t}$$

Back

FICO Scores and Financial Sophistication

- Other literature using FICO scores as a proxy measure for financial sophistication
  - Agarwal, Rosen, and Yao (2016)
  - Amromin, Huang, Sialm, and Zhong (2018)
  - Bhutta, Fuster, and Hizmo (2021)
- Further Analysis:
  - Our results are not driven by income
  - FICO scores are highly correlated with a mistake-based measure of financial sophistication (Calvet, Campbell, and Sodini, 2009)

Back

Econometric Model: Robustness

$$\mathrm{Y}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F\right) + \alpha_j + \sum_m X_i^m + \varepsilon_i$$

where

- α_j = Borrower fixed effects
- All other variables defined as before

Caveats:

- Borrower ID only within the same bank, but not across banks
- Potential spillover effects across cards within borrowers

Back

Descriptive Statistics

	All Cards			Reward	Classic	Multiple Card Sample
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Median	SD	Mean	Mean	Mean
Panel A. Net Reward Variables.						
Reward Card (0/1)	0.55	1.00	0.50	1.00	0.00	0.47
Gross Rewards (in $)	6.07	0.00	23.06	11.06	0.00	3.51
Interest Charges (in $)	17.80	0.00	41.28	20.84	14.09	21.17
Total Fee Charges(in $)	3.37	0.00	12.60	3.87	2.75	3.15
Net Rewards (in $)	−15.09	0.00	48.99	−13.65	−16.84	−20.81
Panel B. Other Credit Card Outcomes.						
Purchase Volume (in $)	478.14	8.74	1534.20	780.01	110.46	285.17
Outstanding Balances (in $)	1619.38	400.00	3113.02	2036.04	1111.97	
Actual Payments (in $)	536.14	85.81	1686.99	844.82	160.16	365.39
APR (in %)	21.99	22.24	5.02	19.87	24.57	22.63
APR (incl. promotions) (in %)	19.43	20.99	8.21	18.08	21.07	19.76
Cash Advance APR	26.48	27.24	2.70	26.60	26.33	26.53
Credit Limit (in $k)	7.76	5.00	8.12	10.58	4.33	6.21
Panel C. Control Variables.						
FICO Score	726.18	738.00	82.03	745.64	702.47	707.73
Borrower Income (in $k)	95.39	62.38	1666.68	109.56	78.13	90.73
Age of Card	6.42	4.00	6.85	6.53	6.30	6.79
Promotion Card (0/1)	0.12	0.00	0.32	0.09	0.15	0.13
Joint Account (0/1)	0.02	0.00	0.14	0.02	0.02	0.01
Deposit Relationship (0/1)	0.20	0.00	0.40	0.29	0.10	0.20
Lending Relationship(0/1)	0.08	0.00	0.27	0.10	0.05	0.08
No. Cards (same bank)	1.75	1.00	0.98	1.62	1.90	2.73
NPL in Last 3 years	0.03	0.00	0.17	0.02	0.04	0.04
Observations	166,205,496	166,205,496	166,205,496	91,271,502	74,933,994	33,913,888

Back

Regression Analysis: Net Rewards (Robustness)

$$\mathrm{Y}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F\right) + \alpha_f + \alpha_w + \alpha_z + \alpha_b + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Net Rewards					
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	6.80***	6.11***	5.11***		1.63***	
	(0.40)	(0.51)	(0.49)		(0.45)	
Reward Card × Sub-Prime				−5.07***		−5.84***
				(0.57)		(0.87)
Reward Card × Near-Prime				−5.14***		−7.73***
				(0.77)		(1.08)
Reward Card × Prime				11.67***		6.67***
				(0.60)		(0.63)
Reward Card × Super-Prime				21.42***		18.98***
				(0.96)		(1.03)
Card Controls	Y	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	-	-
FE: Bank × ZIP × Income	Y	N	-	-	-	-
FE: Bank × ZIP × FICO	N	Y	-	-	-	-
FE: Bank × ZIP × Income × FICO	N	N	Y	Y	-	-
FE: Bank × Borrower	N	N	N	N	Y	Y
Observations	166,205,496	166,205,496	166,205,496	166,205,496	33,913,888	33,913,888
Mean Y	-15.09				-20.79	

Back

Aggregate Net Rewards

In $mn.	Sum Negative Net Rewards (1)	Sum Positive Net Rewards (2)
All Reward Cards	−4050	1290
Sub-Prime	−1110	36
Near-Prime	−1560	139
Prime	−1050	367
Super-Prime	−334	751

- Annual Aggregate Cross-Subsidy = \$1.3 bn.×12 = \$15.5 bn.

Back

Regression Analysis: Net Reward Components

$$\text{Y}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F\right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Gross Rewards		Interest Charges		Total Fee Charges	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	6.99***		1.19***		0.69***	
	(0.46)		(0.17)		(0.11)	
Reward Card × Sub-Prime		1.77***		6.05***		0.79***
		(0.17)		(0.64)		(0.07)
Reward Card × Near-Prime		5.48***		9.90***		0.71***
		(0.34)		(0.81)		(0.15)
Reward Card × Prime		10.02***		−2.27***		0.62***
		(0.47)		(0.25)		(0.14)
Reward Card × Super-Prime		11.56***		−10.50***		0.64***
		(0.45)		(0.59)		(0.09)
Card Controls	Y	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	Y	Y
FE: Bank × ZIP × Income × FICO	Y	Y	Y	Y	Y	Y
Observations	166,205,496	166,205,496	166,205,496	166,205,496	166,205,496	166,205,496
Mean Y	6.07		17.80		3.37	

Back

Regression Analysis: Credit Card Usage

$$\mathrm{Y}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Purchase Volumes		Unpaid Balances	
	(1)	(2)	(3)	(4)
Reward Card	306.91***		−238.10***	
	(29.31)		(46.80)	
Reward Card × Sub-Prime		5.34		397.41***
		(8.27)		(65.26)
Reward Card × Near-Prime		194.80***		754.56***
		(21.40)		(97.24)
Reward Card × Prime		482.25***		64.41
		(32.89)		(51.72)
Reward Card × Super-Prime		597.56***		−336.74***
		(27.65)		(15.87)
Card Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
FE: Bank × ZIP × Income × FICO	Y	Y	Y	Y
Observations	166,205,496	166,205,496	166,205,496	166,205,496

Misallocated Payments Back

Regression Analysis: Net Rewards by Income Group

$$Y_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F\right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Net Rewards					
	Income <50k		Income 50-85k		Income >85k	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	2.53***		4.37***		8.51***	
	(0.26)		(0.36)		(0.80)	
Reward Card × Sub-Prime		−2.04***		−4.89***		−15.03***
		(0.20)		(0.40)		(1.03)
Reward Card × Near-Prime		−0.82**		−4.01***		−12.28***
		(0.48)		(0.61)		(0.86)
Reward Card × Prime		8.11***		10.32***		15.38***
		(0.39)		(0.48)		(0.85)
Reward Card × Super-Prime		12.25***		17.84***		27.86***
		(0.48)		(0.60)		(1.15)
Card Controls	Y	Y	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y	Y	Y
FE: Bank × ZIP × Income × FICO	Y	Y	Y	Y	Y	Y
Observations	59,103,134	59,103,134	53,322,168	53,322,168	53,678,298	53,678,298
Mean Y	-16.92		-16.23		-11.95	

Back

Mis-allocated Payments and Financial Sophistication

- Idea: Measuring financial sophistication based on "mistakes" that consumers make (Calvet, Campbell, and Sodini, 2009)
- We calculate "mis-allocated payments" akin to Gathergood, Mahoney, Stewart, Weber (2019)
- Focus on the sample of borrowers with at least one reward and one classic card at the same bank

Back

Mis-allocated Payments and Financial Sophistication

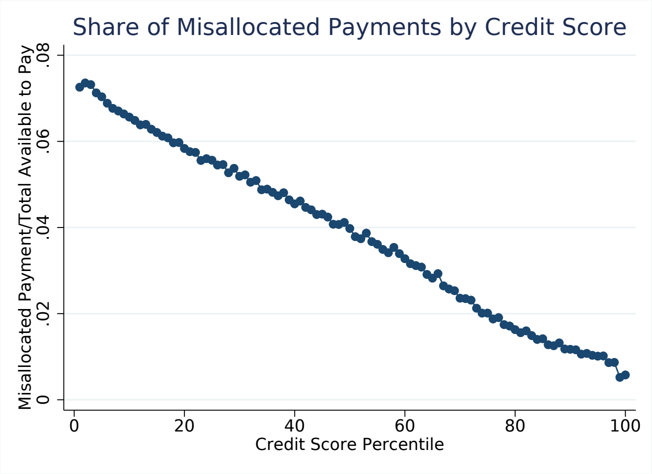
- Rational decision rule:
  - First: Make the minimum payment due on all cards
  - Second: Pay of the card with the highest APR in full
  - Third: Start paying off cheaper cards after
- We rank all cards of borrower i at bank b by their APR
- Calculation of mis-allocated payment (MAP) share

$$\text{MAP Share} = \begin{cases} \frac{\text{Actual Payment Amount}_{i,b} - \text{Optimal Payment Amount}_{i,b}}{\text{Total Payment Amount}_{i,b}} & \text{if } \text{APA}_{i,b} > \text{OPA}_{i,b} \\ 0 & \text{if } \text{APA}_{i,b} \leq \text{OPA}_{i,b} \end{cases}$$

- Interpretation: Share of payments that were incorrectly made on a cheaper card that should have been made on more expensive card(s).

Back

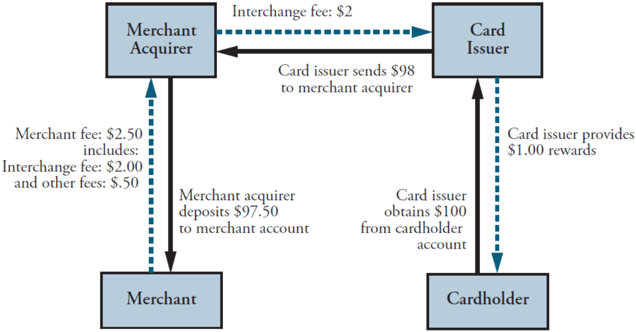
Mis-allocated Payments Across the FICO Distribution



Market Structure of Credit Card Payments

Figure 1

PAYMENT AND FEE FLOWS IN FOUR-PARTY SCHEME CARD NETWORKS



Source: Hayashi (2009)

Back

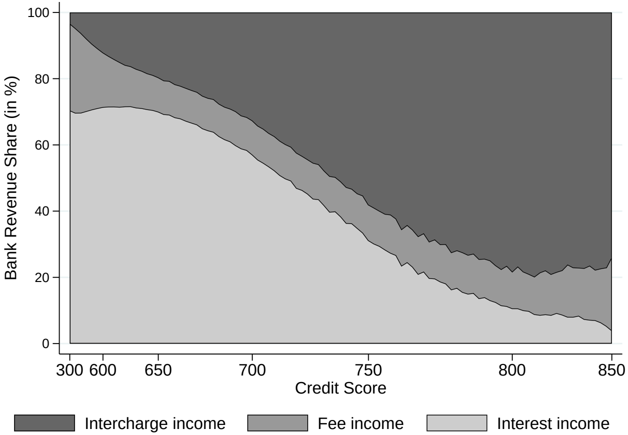
Regression Analysis: APRs and Bank Profits

$$Y_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F\right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	APR (in pp.)		Profits (in $)	
	(1)	(2)	(3)	(4)
Reward Card	−1.87***		4.05***	
	(0.27)		(0.62)	
Reward Card × Sub-Prime		−0.76***		−3.19***
		(0.14)		(1.01)
Reward Card × Near-Prime		−1.62***		14.60***
		(0.30)		(1.17)
Reward Card × Prime		−2.54***		6.15***
		(0.34)		(0.55)
Reward Card × Super-Prime		−2.70***		−0.56
		(0.32)		(0.38)
Card Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
FE: Bank × ZIP × Income × FICO	Y	Y	Y	Y
Observations	192,728,427	192,728,427	192,728,427	192,728,427
Mean Y	21.99		19.43	

Back

Bank Revenue Shares Across the FICO Distribution



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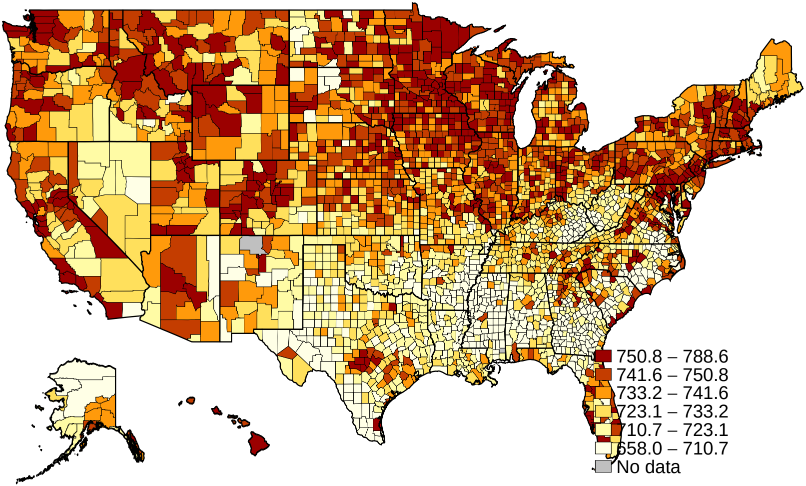
The Geography of FICO Scores



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