Selecting the Optimal Credit Card Portfolio

Remco A. Scheepmaker

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In 30 minutes...

you'll know how to be financially sophisticated and profit from the financially naïve!

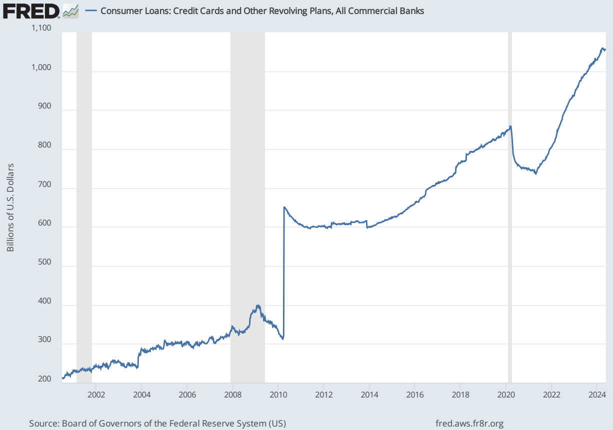
Outline

Why Credit Cards?

- I’m a big credit card nerd!
- A unique hobby that *pays* me money:

The Market for Credit Cards

- Credit cards are also an important part of the economy
  - Consumers spent \$3.2 trillion using credit cards in 2022[1]
  - Total credit card debt passed \$1.1 trillion (82% revolving)
  - \$130 billion charged in interest and fees (2022)



[1] *The consumer credit card market*, CFPB (2023)

Credit Cards Rewards

- Rewards programs can also be beneficial
  - Total rewards earned in 2022: >$40 billion[2]
  - The average account redeemed $167
  - The average American has 3.9 accounts

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Credit Cards Rewards

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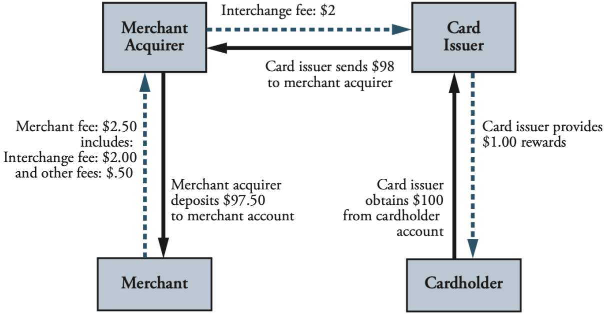
- My project
  - How should different consumers optimize their credit card portfolio?
  - What is the value of this optimal portfolio?
  - What is the marginal benefit of additional cards?
  - Is there an optimal number of cards?

[2] *The consumer credit card market*, CFPB (2023)

The Economics of Credit Card Transactions

- First, *who pays for the rewards?*
- Example of a $100 purchase (from F. Hayashi, 2009):



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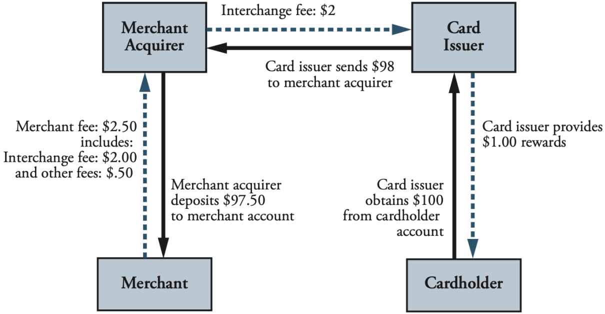

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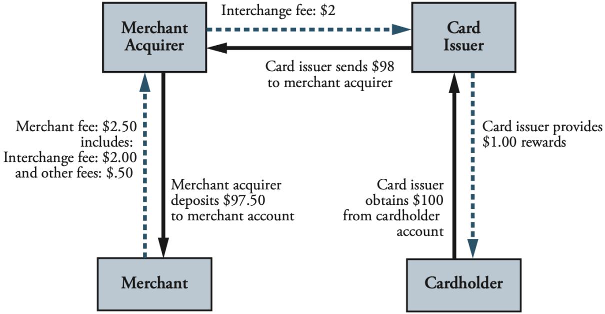


- Merchants likely pass the fees through to *all* customers
- "Credit card rewards programs, are not likely to be efficient (...) rewards may potentially be too generous, lowering overall consumer welfare."

The Reverse Robin Hood Mechanism

- Rewards transfer money from low-income to high-income households (S. Schuh *et al.*, (2010))

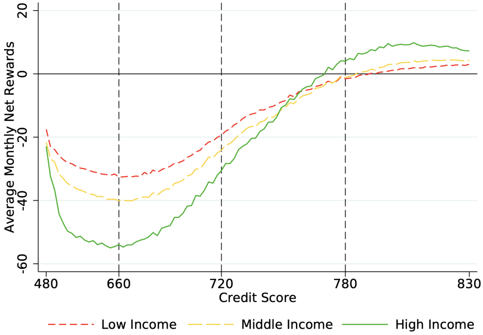
Who Gains and Who Loses from Credit Card Payments? Theory and Calibrations

Scott Schuh, Oz Shy, and Joanna Stavins

Abstract:
Merchant fees and reward programs generate an implicit monetary transfer to credit card users from non-card (or "cash") users because merchants generally do not set differential prices for card users to recoup the costs of fees and rewards. On average, each cash-using household pays $149 to card-using households and each card-using household receives $1,133 from cash users every year. Because credit card spending and rewards are positively correlated with household income, the payment instrument transfer also induces a regressive transfer from low-income to high-income households in general. On average, and after accounting for rewards paid to households by banks, the lowest-income household ($20,000 or less annually) pays $21 and the highest-income household ($150,000 or more annually) receives $750 every year. We build and calibrate a model of consumer payment choice to compute the effects of merchant fees and card rewards on consumer welfare. Reducing merchant fees and card rewards would likely increase consumer welfare.

Financial Sophistication

- S. Agarwal *et al.*, (2023) show this model is incomplete:
  - Redistribution takes place from low to high FICO scores *regardless* of income
  - High-scoring cardholders benefit primarily at the expense of high-income cardholders with low credit scores
  - FICO scores are a proxy for *Financial Sophistication*[3]



[3] The ability of consumers to make informed decisions and avoid mistakes in the use of financial products.

Literature Summary

- Rewards Programs are inefficient
  - There likely exists hidden price action
  - Great! This can be exploited by smart consumers!

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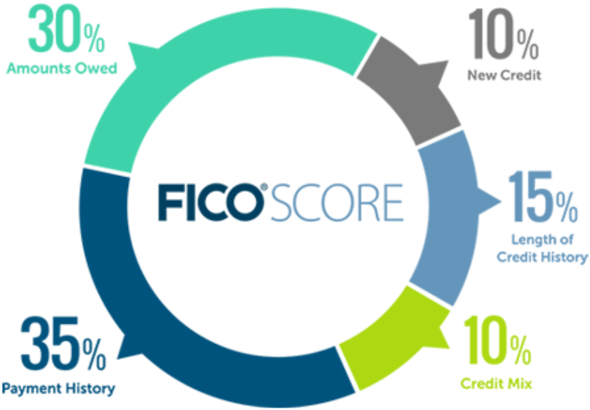
- Rewards Programs are inefficient
  - There likely exists hidden price action
  - Great! This can be exploited by smart consumers!
- Money flows from the naïve to the sophisticated
  - We need to be financially sophisticated before we can benefit

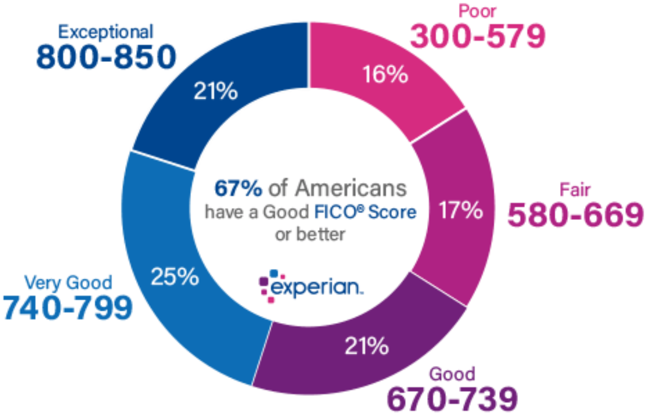
What is a FICO Score?

- A scoring model used by lenders to estimate consumer risk



What is a FICO Score?

- Higher scores are less risky and get better terms and credit cards

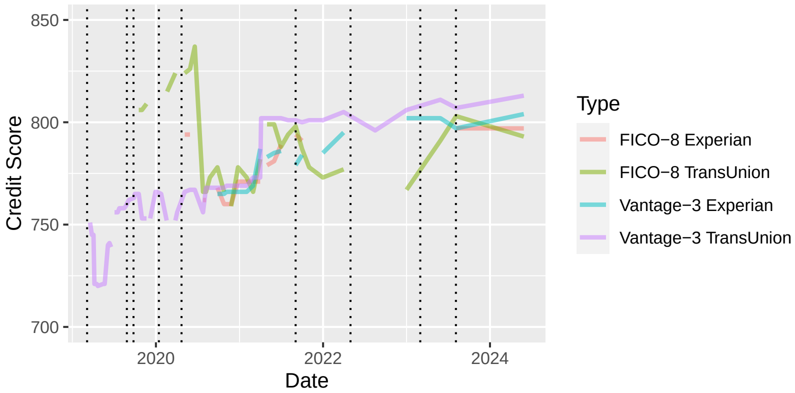


Smart Financial Habits

- Only use credit cards if you can pay them off *in full* the next month
  - Paying $>$ 20% APR interest on revolving balances, negates all benefits!
- Always pay on time (payment history)
- Keep utilization ratio $<$ 10–30% (amount owed)
- Don't apply too often, too quickly (new credit)
- Keep your oldest card open forever (length of credit history)

Myth Debunked

- No, having many cards does *not* ruin your credit score:



Theory – The Problem

- Credit cards reward the user with spend (cash back or points), but some also have static benefits (lounge access, travel credit, free Disney+, etc.) and annual fees
- To maximize the net benefit, how should a financially sophisticated cardholder optimize her credit card portfolio?
- Credit card data is heavily regulated and very private! We need simulations using realistic input data.

Theory – Dynamic Programming

- This is a *Dynamic Program*, which ChatGPT defines as:
  - “A method or algorithm designed to solve problems by breaking them down into **simpler subproblems**, solving each of those subproblems just once, and **storing their solutions**. The key idea is to use past computations to avoid redundant work, which makes the approach efficient. This technique is especially useful for optimization problems where a solution can be constructed incrementally from solutions to subproblems.”

Theory – Dynamic Programming

- Assuming:
  - Spending in N categories x_c $(c = 1, \ldots, N)$
  - Rewards point multiplier per category β_c
  - Point base value v_{base}, travel value v_{travel}, travel redemption fraction η
  - Benefits value V_{benefits} and their use fraction θ

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- Then we have for a single card:
  - Value earned per category:

$$y_c = x_c \beta_c \left[\eta v_{\text{travel}} + (1 - \eta) v_{\text{base}} \right]$$

  - Total value from spending:

$$V_{\text{spend}} = \sum_{c=1}^{N} y_c$$

  - Total net benefit of a *single* credit card:

$$\text{Total benefit} = V_{\text{spend}} + \theta \cdot V_{\text{benefits}} - \text{Fee}$$

Theory – Dynamic Programming

- For multiple cards ($i = 1, \ldots, K$), our algorithm needs to:
  - First select the best single card (**simpler subproblem**)
  - **Store the solution** (best card for each category) and the total net benefit
  - Iterate over all other cards
  - Only keep the card if the total net benefit is higher
  - Replace the best card for each category with the higher value one

Data Needed

- This algorithm requires the following data
- Credit Cards:
  - Point multipliers per category, incl. limits (caps)
  - Estimates on point values (base, travel)
  - Estimates on value of other benefits
  - Annual fees
- Credit Card Users:
  - Spending per category
  - Fraction of high-value point redemptions (travel)
  - Fraction of use of other benefits

Credit Cards Data

- Will be compiled manually for 30–50 popular cards (in progress. . .)
  - cardpointers.com, allcards.com
  - Ignoring airline and hotel cards (subjective, niche benefits)

id	bank	name	fee	benefits	cash_only	base_value	travel_value	travel_other	travel_other_cap	airline_portal	airline_portal_cap	hotel_portal	hotel_portal_cap	car_portal	car_portal_cap	groceries	groceries_cap	dining	dining_cap	gas	gas_cap	online_shopping	online_shopping_cap
1	Amex	Blue Cash Preferred	95	84	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	6	6000	1	0	3	0	1	0
2	Amex	Blue Cash Everyday	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	3	6000	1	0	3	6000	3	6000
3	Amex	Everyday Preferred	95	0	FALSE	0.006	0.02	1	0	2	0	2	0	2	0	3	6000	1	0	2	0	1	0
4	Amex	Everyday	0	0	FALSE	0.006	0.02	1	0	1	0	1	0	1	0	2	6000	1	0	1	0	1	0
5	Amex	Green	150	229	FALSE	0.006	0.02	3	0	3	0	3	0	3	0	1	0	3	0	1	0	1	0
6	Amex	Gold	250	240	FALSE	0.006	0.02	3	0	3	0	1	0	1	0	4	25000	4	0	1	0	1	0
7	Amex	Platinum	695	1044	FALSE	0.006	0.02	5	500000	5	500000	5	0	1	0	1	0	1	0	1	0	1	0
8	Chase	Freedom Unlimited	0	0	FALSE	0.01	0.01	1.5	0	5	0	5	0	5	0	1.5	0	3	0	1.5	0	1.5	0
9	Chase	Sapphire Preferred	95	50	FALSE	0.0125	0.026	2.1	0	5.1	0	5.1	0	5.1	0	1	0	3.1	0	1	0	1	0
10	Chase	Sapphire Reserve	550	360	FALSE	0.015	0.027	3	0	10	0	10	0	10	0	1	0	3	0	1	0	1	0
11	Chase	Amazon Prime	0	0	TRUE	0.01	0.01	1	0	5	0	5	0	5	0	1	0	2	0	2	0	5	0
12	BoA	Premium Rewards	95	120	TRUE	0.01	0.01	2	0	2	0	2	0	2	0	1.5	0	2	0	1.5	0	1.5	0
13	BoA	Travel Rewards	0	0	FALSE	0.01	0.01	1.5	0	3	0	3	0	3	0	1.5	0	1.5	0	1.5	0	1.5	0
14	BoA	Unlimited Rewards	0	0	TRUE	0.01	0.01	1.5	0	1.5	0	1.5	0	1.5	0	1.5	0	1.5	0	1.5	0	1.5	0
15	BoA	Custom Rewards Dining	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000	3	10000	1	0	1	0
17	BoA	Custom Rewards Online	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000	1	0	1	0	3	10000
18	BoA	Custom Rewards Gas	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000	1	0	3	10000	1	0
19	BoA	Custom Rewards Home	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000	1	0	1	0	1	0
20	BoA	Custom Rewards Drug	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000	1	0	1	0	1	0
21	Citi	Double Cash	0	0	TRUE	0.01	0.01	2	0	2	0	2	0	2	0	2	0	2	0	2	0	2	0
22	Citi	Strata Premier	95	0	FALSE	0.0125	0.015	3	0	10	0	10	0	10	0	3	0	3	0	3	0	1	0
23	Citi	Custom Cash Gas	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0	1	0	5	6000	1	0
24	Citi	Custom Cash Groceries	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	5	6000	1	0	1	0	1	0
25	Citi	Custom Cash Dining	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0	5	6000	1	0	1	0
27	Citi	Custom Cash Streaming	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
28	Citi	Custom Cash Drugs	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0

Users Data

- Average budget (percentage per category) from BLS Consumer Expenditure Survey (2022)
- Corrected for non-credit card spend (rent, insurance, etc.)

Table A. Average income and expenditures of all consumer units, 2020-22

Item	2020	2021	2022	Percent change 2020 - 2021	Percent change 2021 - 2022
Number of consumer units (000's)	131,234	133,595	134,090	0.0	0.0
Average Income before taxes	$84,352	$87,432	$94,003	3.7	7.5
Average annual expenditures	$61,332*	$66,928	$72,967	9.1	9.0
Food	7,310*	8,289	9,343	13.4	12.7
Food at home	4,935*	5,259	5,703	6.6	8.4
Food away from home	2,375	3,030	3,639	27.6	20.1
Alcoholic beverages	478	554	583	15.9	5.2
Housing	21,417*	22,624	24,298	5.6	7.4
Owned dwellings	7,473	7,591	8,230	1.6	8.4
Rented dwellings	4,408	4,684	4,990	6.3	6.5
Other lodging	722	983	1,287	36.1	30.9
Lodging on out-of-town trips	318	604	837	89.9	38.6
Apparel and services	1,434	1,754	1,945	22.3	10.9
Transportation	9,826	10,961	12,295	11.6	12.2
Vehicle purchases (net outlay)	4,523	4,828	4,496	6.7	-6.9
Gasoline, other fuels, and motor oil	1,568	2,148	3,120	37.0	45.3
Public and other transportation	263	452	845	71.9	86.9
Healthcare	5,177	5,452	5,850	5.3	7.3
Health insurance	3,667	3,704	3,843	1.0	3.8
Medical services	864	1,070	1,184	23.8	10.7
Entertainment	2,909*	3,568	3,458	22.7	-3.1
Fees and admissions	425	654	833	53.9	27.4
Pets, toys, hobbies, and playground equipment	859	969	908	12.8	-6.3
Other entertainment supplies, equipment, and services	576*	925	698	60.6	-24.5
Personal care products and services	646	771	866	19.3	12.3
Reading	114	114	117	0.0	2.6
Education	1,271	1,226	1,335	-3.5	8.9
Tobacco products and smoking supplies	315	341	371	8.3	8.8
Miscellaneous	907	986	1,009	8.7	2.3
Cash contributions	2,283	2,415	2,755	5.8	14.1
Personal insurance and pensions	7,246	7,873	8,742	8.7	11.0

Item	Expenditure	Percentage
everything_else	$7,786	20.18%
groceries	$6,362	16.49%
dining	$4,222	10.94%
gas	$3,120	8.09%
utility	$3,117	8.08%
home_improvement	$2,606	6.76%
online_shopping	$1,881	4.87%
drug_store	$1,481	3.84%
travel_other	$1,460	3.78%
phone	$1,431	3.71%
streaming	$1,020	2.64%
department_store	$973	2.52%
entertainment	$833	2.16%
cable_internet	$698	1.81%
hotel_portal	$644	1.67%
airline_portal	$423	1.10%
car_portal	$394	1.02%
office_supplies	$128	0.33%

Using the Data for Simulations

- First test if the algorithm works (Sensitivity Analysis)
  - Assume low-vs-high income (e.g. $50k vs $150k)
  - Assume spending 41% on credit cards (BLS survey)
  - Assume $\eta, \theta \in [0, 0.5, 1.0]$
  - How does the net benefit change with these assumptions and number of cards?
- If successful, attempt Monte-Carlo Simulations
  - Sample income from log-normal distribution
  - Sample η, θ from uniform distributions

Summary & Conclusions

- Financially sophisticated credit card users can benefit from inefficiencies in rewards programs by using the right credit cards
- By using a Dynamic Program and Monte Carlo Simulations I aim to quantify this benefit for the average spending card user
- Next week we'll talk more about the data!

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