Who Pays For Your Rewards? Redistribution in the Credit Card Market*

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Abstract: We study the redistributive effects of reward programs in consumer credit markets, where salient benefits often mask shrouded costs. Using granular information on over 200 million U.S. credit cards and comparing reward cards with otherwise similar non-reward cards, we find that sophisticated individuals profit at the expense of naïve consumers regardless of their income. To probe the underlying mechanisms, we exploit bank-initiated credit limit increases and show that rewards stimulate spending across all consumers but leave only naïve individuals with higher unpaid balances. Naïve consumers with multiple cards also follow a suboptimal balance-matching heuristic when repaying, incurring unnecessary costs. Banks incentivize reward cards by offering lower APRs than on non-reward cards, profiting from naïve consumers through interest and fee charges and from sophisticated individuals through interchange income. We estimate an aggregate annual redistribution of $15 billion from less to more educated, poorer to richer, and high to low minority areas.

Keywords: household finance; credit cards; financial sophistication; rewards
JEL Codes: G21; G40; G51; G53

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1 Introduction

When individuals make financial decisions, behavioral biases such as time-inconsistent preferences or heuristic-driven behavior often lead to costly mistakes (e.g., Campbell, 2006; Gomes et al., 2021). Banks, in response, can design financial products to exploit these biases, combining salient benefits with shrouded costs (DellaVigna and Malmendier, 2004; Heidhues and Kőszegi, 2010, 2017). While naïve consumers frequently underestimate these costs and incur considerable losses, sophisticated individuals often extract net benefits. Such financial products can thus generate an implicit redistribution from naïve to sophisticated consumers (Gabaix and Laibson, 2006).

Despite these theoretical predictions, empirically quantifying the extent of redistribution across consumers in retail financial markets is challenging. In this paper, we use credit card rewards as an ideal laboratory to investigate this issue.[1] Comparing reward cards with otherwise similar non-reward cards, we find that sophisticated individuals profit from reward programs at the expense of naïve consumers, with interest and fee charges exceeding earned rewards for the latter. Notably, our results are not driven by income and are thus inconsistent with a reverse Robin Hood hypothesis. Instead, we find that reward programs induce higher unpaid credit card debt and exacerbate suboptimal repayment behavior among naïve consumers. On the supply side, banks steer both consumer types towards reward cards by offering lower interest rates than on otherwise similar non-reward cards. Yet, reward cards still yield higher profits for banks, as naïve consumers incur higher interest charges from larger unpaid balances, while sophisticated consumers generate higher interchange income through increased spending. In aggregate, we estimate an annual redistribution of $15 billion from less to more educated, poorer to richer, and high to low minority areas.

For our study, we use comprehensive supervisory credit card data from the Federal Reserve Board's Y-14M reports, which encompass over 200 million U.S. credit card accounts. This data set contains detailed monthly account-level information and is therefore uniquely suited to study redistribution across different consumers. Specifically, it allows us to compute a cardholder's monthly net reward, defined as the dollar value (cashback cards) or dollar-equivalent value (miles or points cards) received in rewards minus the dollar value of interest and fee charges, thus capturing both the benefits and the costs of credit card usage.

We start by investigating whether reward credit cards imply redistribution between consumers across the FICO score distribution. To this end, we compare the outcomes of reward

[1] Reward credit cards—which offer points, miles, or cashback—are a ubiquitous feature of credit card markets, particularly in Anglo-Saxon countries. For instance, reward credit cards accounted for 60 percent of all new credit card originations in the U.S. in 2019 (CFPB, 2019).

cards to those of similar non-reward cards across cardholders in the *same FICO and income percentiles*, living in the *same ZIP code*, and who are clients at the *same bank*, while further controlling for an extensive set of card- and consumer-level characteristics. We find that for sub-prime (with a FICO score below 660) and near-prime (660 to 720) cardholders, monthly net rewards are on average \$5.4 and \$6.8 lower, respectively, on reward cards relative to similar non-reward cards. For prime (720 to 780) and super-prime (above 780) cardholders, monthly net rewards are on average \$7.3 and \$16.0 higher, respectively. This result is driven by both the cost and the benefit margin of net rewards. Super-prime cardholders earn \$9.5 in rewards and pay \$7.1 less in interest on reward cards than on non-reward cards. In contrast, sub-prime consumers earn only \$1.8 in rewards but pay \$6.4 more in interest. Thus, high-FICO individuals profit from reward programs while low-FICO cardholders lose both in absolute terms—with interest and fee charges exceeding earned rewards—and relative to comparable non-rewards cards.

Next, we study whether the redistribution across FICO scores is driven by differences in cardholders' income, suggesting a transfer from poor to rich consumers. Indeed, credit card rewards are often framed as a reverse Robin Hood mechanism in which the poor subsidize the rich.[2] Our results, however, show that this explanation is at best incomplete. Since FICO scores and income are weakly correlated, as documented in Beer et al. (2018) and as shown in our data, we can disentangle these two margins. We find evidence of redistribution from low- to high-FICO consumers within all income groups. High-FICO cardholders, especially those with higher income but also those with lower income, profit from reward cards at the expense of low-FICO cardholders from all income groups.

As our findings are inconsistent with the reverse Robin Hood hypothesis, we next investigate whether differences in cardholders' financial sophistication can explain our results. Since FICO scores are based on an individual's payment history and outstanding debt relative to available credit, they largely capture the same type of credit card behavior that is associated with a lack of financial sophistication e.g., overindebtedness and suboptimal repayment behavior. FICO scores might thus serve as a proxy for financial sophistication (e.g. Agarwal et al., 2016; Amromin et al., 2018; Bhutta et al., 2024; Gibbs et al., 2024).[3]

[2]See, for example, "Credit cards take from poor, give to the rich" (Wall Street Journal, 2010) and "How credit card companies reward the rich and punish the rest of us" (Brookings, 2019).

[3]We define financial sophistication as the ability of consumers to avoid mistakes when using financial products. Credit scores, however, can be influenced by factors other than financial sophistication, such as adverse life events (Gibbs et al., 2024). To address this concern, we show that FICO scores are strongly correlated with tangible mistake-based measures of financial sophistication. In addition, our results hold when excluding consumers likely to have faced adverse life events such as a job loss or a medical emergency.

We first provide quasi-experimental causal evidence that reward credit cards induce low-FICO consumers to accumulate unpaid credit card balances. To this end, we compare the spending and borrowing responses of consumers who received a *bank-initiated* credit limit increase on reward cards to those who received a limit increase on non-reward cards in the same month. We find a stronger increase in spending on reward cards across all FICO groups in response to such an increase in available credit. However, while prime and super-prime consumers exhibit a commensurate increase in credit card repayments, this is not the case for sub-prime and near-prime consumers. As a result, there is a stronger increase in unpaid balances on reward cards only among low-FICO consumers. This pattern is consistent with the documented tendency of naïve consumers to overborrow on their credit cards (Lusardi and Mitchell, 2014; Lusardi and Tufano, 2015) and thus in line with the interpretation of FICO scores as a proxy for financial sophistication.

In a separate exercise, we also show that FICO scores are associated with mistake-based measures of financial sophistication, as suggested by Calvet et al. (2009) and Jørring (2024), and that this relationship is more pronounced for reward cards. Focusing on individuals with multiple credit cards at the same bank, we compute the share of misallocated credit card repayments as in Ponce et al. (2017) and Gathergood et al. (2019).[4] We find that this share is strongly decreasing in FICO scores and, for sub-prime and near-prime cardholders, larger for reward cards than for similar non-reward cards. We also show that low-FICO consumers are more likely to follow a suboptimal balance-matching heuristic when repaying their credit cards, which is also consistent with the documented suboptimal repayment behavior of naïve consumers (Kuchler and Pagel, 2021).

Having documented that credit card rewards lead to redistribution from naïve to sophisticated consumers, we turn to the supply side and study banks' pricing and the profitability of reward cards. Despite banks incurring additional expenses by paying out rewards, we show that they offer lower annual percentage rates (APRs) on reward cards than on similar non-reward cards across the entire FICO distribution, suggesting that banks steer consumers towards reward cards. Nonetheless, we find that banks' profits are higher on reward cards than on non-reward cards across all FICO scores.[5] How do banks profit more from reward cards despite additional expenses and lower APRs? We document substantial differences re-

[4]The optimal interest-minimizing repayment behavior among consumers who do not repay all cards in full is to first make the minimum required payment on all cards, then repay as much as possible on the card with the highest interest rate, and then allocate further payments to subsequently cheaper cards.

[5]We define banks' profits on credit cards as the sum of income from interest payments, fee payments, and interchange fees, minus reward expenses, loan loss provisions, funding costs, and operational expenses (Adams et al., 2022).

garding banks' sources of revenue across consumer types. For naïve cardholders, more than 60 percent of banks' revenues stem from interest income due to higher unpaid balances, while for sophisticated cardholders, up to 80 percent stem from interchange income. Thus, higher interest payments from naïve consumers and higher interchange income from sophisticated consumers make reward programs profitable for banks across the FICO distribution.

Finally, we study the geographic distribution of net rewards across ZIP codes and investigate whether the large aggregate transfer induced by credit card rewards is associated with socio-demographic characteristics. We find that net rewards are on average higher in ZIP codes that are more educated, richer, and have a lower share of minorities.[6] The redistribution through credit card reward programs therefore widens existing spatial disparities.

We contribute to several strands of the literature. First, we analyze empirically the redistribution from naïve to sophisticated consumers, which has so far largely been studied theoretically. Consistent with our findings, DellaVigna and Malmendier (2004), Eliaz and Spiegler (2006), and Heidhues and Kőszegi (2010) show how contract designs in the credit card market can exploit the time-inconsistent preferences of naïve consumers who end up overborrowing. Overconfidence can further exacerbate such behavior (Grubb, 2009, 2015). In Gabaix and Laibson (2006) and Heidhues and Kőszegi (2017), such products benefit sophisticated at the expense of naïve consumers and the latter cross-subsidize the former. We add to this literature by validating and empirically quantifying these theoretical predictions.

In the context of mortgage markets, Fisher et al. (2024), Zhang (2024), and Berger et al. (2024b) use structural models to quantify cross-subsidies from less to more attentive borrowers induced by refinancing inertia. However, for complex financial products, such as mortgages, optimal behavior depends on consumers' risk aversion, economic expectations, among other hard-to-measure factors. Our paper, in contrast, studies redistribution in the credit card market induced by reward programs. Our data enable us to readily quantify the costs (interest and fee payments) and, uniquely, also the benefits (rewards) of financial product usage in monetary terms, providing an ideal empirical setting to estimate the redistribution from naïve to sophisticated consumers.

Second, we contribute to the literature on reward credit cards, which have received considerable attention by both policymakers and the general public, particularly in recent years.[7] Most papers so far have focused on interchange fees as a source of funding for credit card

[6]While our card-level analysis reveals that the redistribution from naïve to sophisticated consumers occurs regardless of income, we still find a redistribution from high- to low income ZIP codes at the aggregate level, as FICO scores and income are spatially correlated.

[7]See, for instance, New York Times (2023), Wall Street Journal (2023), and Politico (2023) for a general discussion of credit card rewards, as well as The Economist (2024) and Fortune (2025) for a discussion of how a proposed cap on credit card interest rates could affect reward programs.

rewards. Specifically, Schuh et al. (2010) and Felt et al. (2023) report a monetary transfer from cash- to card-users and thereby from low-income to to high-income households. Our study, in contrast, focuses on the redistribution within credit card users, which is, as we argue, an increasingly more important margin. We show that the relevant transfer is from naïve to sophisticated consumers rather than across income cohorts.

More generally, access to unsecured credit among low-income and unemployed individuals has grown significantly over the past few decades (Livshits et al., 2016; Herkenhoff, 2019), at least in part driven by increased competition in the credit card market (Herkenhoff and Raveendranathan, 2024). Our findings complement this literature by showing that financial sophistication plays a key role in determining who benefits from this market development. Indeed, the proliferation of reward programs over past decades, especially after the 2009 CARD Act, introduces an additional layer of redistribution that can persist even in competitive markets, potentially limiting the gains for less sophisticated consumers. Furthermore, the 2009 CARD Act restricted banks' ability to adjust interest rates on the basis of new information about a consumer's risk (Nelson, 2024). Our paper suggests that reward programs may have emerged as an alternative non-interest pricing mechanism—redistributing costs and benefits based on borrowing behavior, where sophisticated consumers benefit while naïve consumers subsidize rewards through interest and fee charges. Importantly, the supply-side analysis in our paper also complements the findings of Ru and Schoar (2023), who show that banks exploit the behavioral biases of consumers by saliently advertising reward programs in credit card offers while shrouding back-loaded payments.

Finally, by documenting a large redistribution through credit cards rewards, our analysis contributes to the literature that highlights the role of the financial system in driving wealth inequality (Lusardi et al., 2017; Bach et al., 2020; Campbell et al., 2019). In particular, our finding that reward programs redistribute income from naïve to sophisticated consumers is related to existing studies that link heterogeneity in asset returns with measures of financial literacy (Deuflhard et al., 2019) and financial sophistication (Fagereng et al., 2020).

2 Credit Card Rewards Programs

Credit card rewards—which can take the form of cashback, miles, or points—are loyalty programs by banks which offer various benefits to cardholders per dollar spent on the credit card. Cashback cards refund a small percentage amount of the net purchase volume (usually between 0.5 and 3 percent), while miles and points can be redeemed at frequent flyer programs (miles cards) or, more generally, at partnering airlines, hotels, or retailers (points cards). Reward credit cards are an ubiquitous and increasingly important aspect of con-

sumer finance, accounting for over 60 percent of all new credit card originations in the United States (CFPB, 2019). In 2019, the largest U.S. banks paid out $35 billion in rewards. Since then, reward credit cards have grown both in complexity and importance, accounting for three-quarters of all general-purpose credit cards by the end of 2022 (CFPB, 2023). While historically concentrated among individuals with higher credit scores, particularly before the 2009 CARD Act, reward card usage is expanding most rapidly among subprime and near-prime consumers (CFPB, 2023). For cardholders, credit card rewards are an opportunity to earn money or perks with the use of their credit cards. For banks, credit card rewards are a mechanism to incentive consumers to adopt and increase the usage of the banks' credit card products (Ching and Hayashi, 2010; Han, 2023).

Other than the cardholder and the card issuer, the market underlying credit card payments and rewards typically involves three parties: (i) the merchant, (ii) the merchant acquirer, and (iii) the card network.[8] Following Felt et al. (2023), consider the example of a cardholder making a $100 purchase with a reward credit card. This payment initially flows from the cardholder to the card-issuing bank, which in turn rewards the cardholder with, for instance, $1 in cashback, miles, or points. The card issuer then retains a $2 interchange fee and sends the remaining $98 to the merchant acquirer, which in turn pays a $0.15 network fee to the card network. The merchant acquirer subsequently sends $97.70 to the merchant, not only passing through interchange and network fees, but also additionally charging a merchant service charge ($0.15). Thus, merchants only receive a fraction of the initial purchase amount and can potentially respond by increasing retail prices, implying that credit card rewards might to some extent be funded by cash and debit card users who pay higher prices without receiving any rewards to compensate (Schuh et al., 2010; Felt et al., 2023).

Another source of funding for credit card rewards, however, are interest payments from credit cardholders with unpaid outstanding balances as well as fees e.g., late and overlimit fees. Credit cards as a payment device have become increasingly popular over recent years. While in 2008 cash accounted for over 30 percent of consumer payments and credit cards for only 17 percent, in 2019 the share of credit card payments (25 percent) exceeded the share of cash payments (22 percent) for the first time (Foster et al., 2021). Moreover, in 2019, the largest U.S. banks reported $89.7 billion in interest income and $9.9 billion in fee income from credit cards, compared to $41.3 billion income from interchange fees. From the banks' perspective, interest and fees therefore constitute a substantially larger share of income than interchange fees. Overall, the redistribution within credit card users has likely become more important than the transfer from cash to card users in recent years.

[8]See also Hayashi (2009), Shy and Wang (2011), Felt et al. (2023), and Wang (2024) for further discussion of the underlying market structure of credit card payments and rewards.

Contrasting the $34.8 billion in rewards expenses with the combined $99.6 billion earned through interest and fee payments suggests that credit card rewards constitute a substantial annual transfer. These aggregate numbers, however, are neither informative about the extent of the redistribution—since cardholders can simultaneously receive rewards and pay interest or fees—nor about which type of consumers benefit and lose from using reward credit cards. In this paper, we study these questions using comprehensive and granular data on individual credit card accounts.

3 Data and Summary Statistics

3.1 Data

We obtain account-level data on consumer credit cards from the Federal Reserve Board's FR Y-14M reports. These reports require large U.S. bank holding companies with at least $100 billion in total assets to report detailed information on individual credit card accounts on a monthly basis. Our data contain information on 19 banks, which cover a large portion of the market and account for 70 percent of aggregate outstanding balances on consumer credit cards (CFPB, 2019). For our main empirical analysis, we obtain card-level data on accumulated rewards, interest and fee charges, purchase volumes, repayment amounts, outstanding balances, FICO credit scores, credit limits, and further card characteristics. We also obtain data on cardholders' ZIP code and income, as well as on the card issuing bank.[9]

Our main outcome variable of interest intents to capture the benefits minus the costs of credit card usage. To this end, we construct the variable *Net Rewards* which subtracts the amount of interest and fee charges on card i in month t from the rewards earned on the card during the same period:[10]

$$\text{Net Rewards}_{i,t} = \text{Rewards}_{i,t} - \text{Interest Charges}_{i,t} - \text{Total Fee Charges}_{i,t} \tag{1}$$

Cardholders with positive net rewards thus earn money with the use of credit cards, while cardholders with negative net rewards pay for the use of credit cards. Our definition of net

[9]See Berger et al. (2024a) for a recent paper also using the Y-14M data set and Agarwal et al. (2015) and Agarwal et al. (2018) for papers using the Credit Card Metrics data set assembled by the U.S. Office of the Comptroller of the Currency (OCC)—the predecessor of the Y-14M data set. A detailed description and a list of all variables included in the dataset, see the Y-14M website of the Federal Reserve.

[10]While our dataset does not contain the amount of monthly rewards, we observe the amount of accumulated rewards as of the reporting month net of redeemed rewards. Online Appendix (A) explains the estimation of monthly rewards from the variables in our data set.

rewards includes the cost of credit card borrowing in the form of interest charges, but not the benefits of borrowing, which depend on cardholders' unobservable demand for credit. Our empirical strategy, however, compares reward to non-reward cards and a dollar borrowed on the former is, ceteris paribus, as good as a dollar borrowed on the latter.[11] Thus, the utility benefits from borrowing do not differ between reward and non-reward cards and should not drive our results.

The rewards in our data come in the form of either cashback, miles, or points. While cash rewards are denominated in dollar to begin with, the Y-14M data report the "total equivalent dollar amount" also for reward cards that offer miles or points. One limitation of our data is that the reward variable does not capture non-pecuniary rewards associated with reward credit cards, such as airport lounge access or travel insurance. In that respect, what we measure is a lower bound of cardholders' net rewards. The variable total fee charges is defined as the sum of the following incurred fees: late fees, over limit fees, non-sufficient funds fees, cash advance fees, debt suspension fees, balance transfer fees, and other fees. Importantly, total fee charges also include the monthly equivalent of the annual card-holding fee. Our analysis also makes use of cardholders' income. The income in the data is self-reported. We use the most recently updated income or, if not available, the income at card origination.[12]

The dataset is very large with overall more than 400 million card-level observations per month. Other studies using these data therefore usually employ stratified card-level samples of, for example, 0.5 percent (Berger et al., 2024a). Our identification strategy, however, relies on an extremely granular set of fixed effects and requires a large number of observations. Thus, our analysis mostly focuses on the cross section of all credit cards in March 2019, a month not subject to seasonal effects in consumption and not affected by the COVID-19 pandemic.[13] We keep all observations for (i) general purpose and private label (ii) unsecured (iii) consumer credit cards with (iv) a revolving feature and with non-missing data on (v) card, customer, bank, period, and ZIP code identifiers, respectively.[14] This

[11] While differences in interest rates can yield rational differences in demand for credit card borrowing between reward and non-reward cards, we conduct a number of tests to show that our results are not driven by such interest rate differentials.

[12] Besides self-reported income being an imperfect measure for actual income (Mian and Sufi, 2017), one caveat is that cardholders infrequently update their income on existing cards. We address this issue, showing similar results for credit cards originated less than 1 year prior to the analysis.

[13] Our results are qualitatively identical and quantitatively very similar when replicating the analysis on all other months in 2019.

[14] This procedure excludes (i) small business and corporate cards, (ii) cards where any portion of the credit line is secured by collateral, (iii) non-consumer cards, and (iv) cards where the entire balance or part of the balance is required to be repaid in full at the end of the billing cycle.

Table 1: **Summary Statistics**

This table presents card-level summary statistics as of March 2019, for all call cards in our sample (Columns 1 to 3), and separately for reward and non-reward cards (Columns 4 and 5). Panel A presents variables related to the calculation of net rewards (as defined in Equation 1). Panel B presents other card-level outcome and control variables used in our analysis.

	All Cards			Reward	Non-Reward
	(1)	(2)	(3)	(4)	(5)
	Mean	Median	SD	Mean	Mean
Panel A. Net Reward Variables					
Rewards (in $)	4.69	0.00	20.42	9.30	0.00
Interest Charges (in $)	14.38	0.00	37.91	18.34	10.36
Fee Charges (in $)	2.64	0.00	11.01	3.33	1.93
Net Rewards (in $)	-12.33	0.00	44.41	-12.37	-12.29
Panel B. Other Variables					
APR (in %)	20.63	21.49	7.15	18.64	22.64
Bank Profits (in $)	14.53	1.11	232.94	22.54	6.39
FICO Score	729.60	742.00	75.65	743.22	715.77
Borrower Income (in $k)	88.44	60.00	1863.36	98.02	78.71
Credit Limit (in $k)	7.37	5.00	7.90	10.42	4.28
Amount Past Due (in $)	10.26	0.00	172.45	8.19	12.37
Age of Card (in years)	7.43	4.83	7.36	7.61	7.24
Joint Account (in %)	2.31	0.00	15.03	2.57	2.06
Fraud Flag (in %)	0.34	0.00	5.83	0.45	0.23
Deposit Relation (in %)	18.87	0.00	39.13	27.95	9.66
Lending Relation (in %)	7.59	0.00	26.49	10.61	4.52
Number of Cards	2.11	2.00	1.25	1.89	2.34
Workout Program (in %)	0.55	0.00	7.41	0.49	0.62
Bankruptcy Flag (in %)	0.29	0.00	5.42	0.21	0.38
Observations		237,573,278		119,730,353	117,842,925

sample construction procedure results in an initial sample of about 348 million credit cards as of March 2019.

3.2 Summary Statistics

Table 1 presents card-level summary statistics as of March 2019 for all cards in our sample (n=237,573,278), as well as separately for reward cards (n^R=119,730,353) and non-reward cards (n^N=117,842,925).[15] Panel A presents variables related to the calculation of net rewards. The average reward card earns $9 in monthly rewards and the average non-reward card—by definition—zero. However, reward cards also exhibit on average higher interest

[15]Our empirical strategy, as discussed in Section 4.1, requires at least one reward card and one non-reward card within each fixed effects cluster. This reduces our sample from 348 million to 238 million card-level observations, which we take as our main sample throughout the paper.

charges than non-reward cards ($18 versus $10) and higher fee payments ($3 versus $2). Thus, on aggregate, the average reward card yields a (negative) net reward of -$12—the same as the average non-reward card.

Panel B presents other card-level variables. On average, reward cards have lower APRs than non-reward cards (19% versus 23%), yield higher bank profits per card in a given month ($23 versus $6), and have higher credit limits ($10 thousand versus $4 thousand).[16] These card-level differences, however, are not necessarily due to differences between the two types of credit card products, but could conceivably be driven by differences in consumers who choose to use reward cards and non-reward cards, respectively. Cardholders of reward cards have, on average, higher FICO scores than cardholders of non-reward cards (743 versus 716) and earn a higher annual income ($98 thousand vs. $79 thousand). The remainder of Panel B provides further summary statistics for the control variables in our regressions.

4 Redistribution in the Credit Card Market

4.1 Empirical Approach

To quantify the redistribution between consumers in the credit card market, and to understand if credit card rewards are a driver of this redistribution, we compare credit card outcomes between reward cards and non-reward cards with similar card- and cardholder characteristics across the FICO distribution.

Let Y_i be an outcome for credit card account i issued by bank b to cardholder j. Our baseline regression specification is then given by:

$$\mathrm{Y}_{ibj} = \sum_{F} \left(\delta^{F} \times \text{Reward Card}_i \times D_j^{F}\right) + \alpha_{b,z,w,f} + \sum_{m} X_i^{m} + \sum_{n} Z_j^{n} + \varepsilon_{ibj} \qquad (2)$$

where *Reward Card* is a dummy variable which takes the value 1 for reward cards and 0 for non-reward cards; D^F is a battery of FICO bucket dummy variables which take the value of 1 for sub-prime cardholders (with a FICO score below 660), near-prime cardholders (600-720), prime cardholders (720-780), and super-prime cardholders (above 780), respectively.[17] Our coefficients of interest, δ^F, capture differences in credit card outcomes between reward and non-reward cards. To make this comparison meaningful, we compare reward cards

[16] We describe the calculation of card-level bank profits in detail in Section 7.2.

[17] To minimize endogeneity concerns arising from the joint determination of net rewards and FICO scores (e.g., due to high unpaid balances), we use FICO scores as of March 2018, one year prior to our data on credit card outcomes. In unreported results, we find even stronger magnitudes when using FICO scores as of March 2019.

with very similar non-reward cards by including interacted fixed effects at the Bank × ZIP code × Income percentile × FICO percentile level ($\alpha_{b,z,w,f}$). That is, we compare credit card outcomes between reward and non-reward cards for cardholders in the *same FICO percentile*, the *same income percentile*, living in the *same ZIP code*, which are clients at the *same bank*. This specification yields 73.6 million populated fixed effects cluster.

In addition, we control for the following card-level characteristics X: the credit limit, the amount past due, the age of the card, a joint account indicator which takes the value of 1 if the account has more than one primary obligor, a fraud flag indicator which takes on the value of 1 if the account is currently frozen due to potential fraud, and a workout program indicator which takes on the value of 1 the account entered into any type of workout program. We further control for cardholder-level characteristics Z: a deposit relationship indicator which takes on the value of 1 if the cardholder has a deposit relationship with the same bank, a lending relationship indicator which takes on the value of 1 if the cardholder has a lending relationship with the same bank, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator which takes on the value of 1 if the cardholder has completed or is in an ongoing bankruptcy process.

4.2 Net Rewards

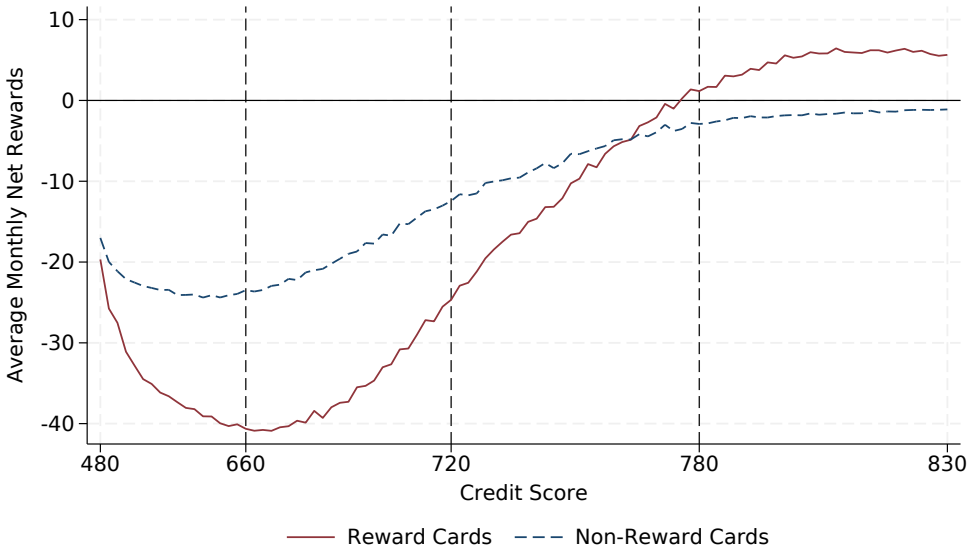
Figure 1 illustrates the magnitude of net rewards across the FICO distribution and point to a clear redistribution between cardholders. For cardholders with super-prime scores (above 780), net rewards are on average positive for reward cards and slightly negative for non-reward cards.[18] These consumers earn money with the use of reward cards, as the monetary benefits outstrip their costs. This pattern is reversed for consumers at the lower end of the FICO distribution. For cardholders with sub-prime (below 660) and near-prime (below 720) scores, net rewards are around -$40 for reward cards and -$25 for non-reward cards. Thus, low-FICO cardholders on average lose money with reward cards, both in absolute dollar terms and relative to non-reward cards.

This descriptive pattern might be driven by differences between individuals with low and high FICO scores, regardless of the type of card they use. To control for these differences, Table 2 presents the estimation results of Equation (2). All specifications include card- and cardholder control variables. To make the comparison as homogeneous as possible in terms of individual characteristics, we increasingly saturate the model with interacted fixed effects. All specifications show that net rewards are significantly higher for reward cards than for

[18]Note that the net rewards of non-reward cards can—by definition—at best be zero if consumers incur no interest or fee charges.

Figure 1: **Net Rewards Across FICO Score Percentiles**

This figure illustrates the dollar magnitude of average net rewards across the FICO distribution, separately for reward cards (solid red line) and non-reward cards (dashed blue line). For each card type, we plot the average net reward for 100 equal-sized FICO buckets between 480 and 830. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our baseline sample of 238 million credit cards in March 2019.



similar non-reward cards. The coefficient of our preferred and most saturated specification in column (3) indicates that a reward card, on average, yields a $3.5 higher net reward than a very similar non-reward card.[19]

This average net reward differential between reward and non-reward cards, however, masks important differences between cardholders across the FICO distribution. Consistent with Figure 1, column (4) shows that net rewards for sub-prime and near-prime cardholders are between $5.4 and $6.8 lower on reward cards than on similar non-reward cards. These magnitudes are economically significant and amount to -4.7% of the average monthly credit card spending for subprime cardholders ($113.1) and to -2.9% for near-prime cardholders ($233.4). On the other end of the FICO distribution, net rewards turn positive and are, on average, $7.3 (1.7% of average credit card spending) and $16.0 (3.0%) higher for prime and

[19]The mean (median) number of cards within each fixed effects cluster in column (3) is 4.79 (3). To ensure that our results are not driven by fixed effects cluster with only a few cards, Table A1 provides a robustness check in which we drop all clusters with less than five cards. Our results remain largely unchanged.

Table 2: **Net Rewards: Baseline Results**

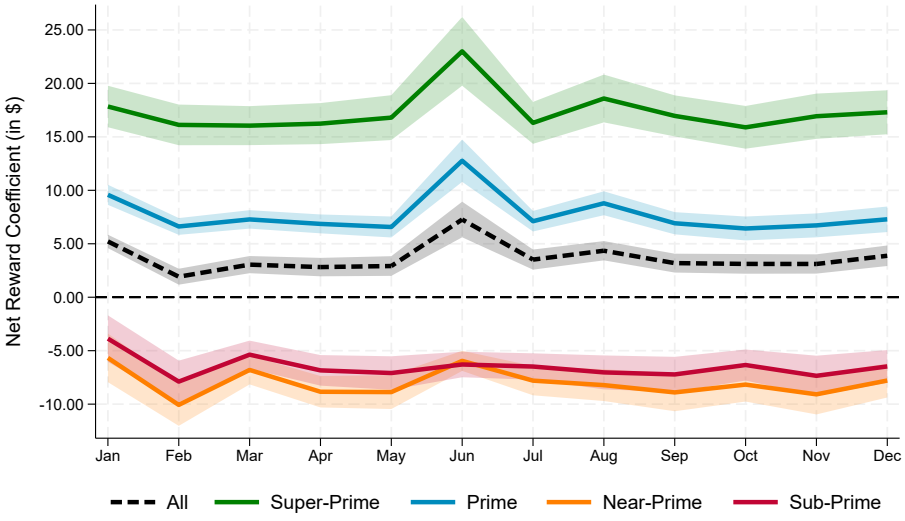
This table presents the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section 4.1, where the outcome variable is the net reward of card i as defined in Equation (1) in Section 3. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net Rewards			
	(1)	(2)	(3)	(4)
Reward Card	4.66***	3.88***	3.48***	
	(0.30)	(0.37)	(0.38)	
Reward Card × Sub-Prime				-5.37***
				(0.7)
Reward Card × Near-Prime				-6.80***
				(0.69)
Reward Card × Prime				7.28***
				(0.44)
Reward Card × Super-Prime				16.05***
				(0.93)
Card Controls	Y	Y	Y	Y
Cardholder 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	237,573,278			

super-prime cardholders, respectively. Thus, while reward cards are more beneficial than non-reward cards on average, only high-FICO consumers gain from them, while low-FICO consumers would incur less net losses choosing non-reward cards, other things equal.[20]

[20]To show that our regression results are not driven by our threshold values for the different FICO buckets, Figure A1 provides a coefficient plot which plots the coefficients δ^F alongside the 95% confidence intervals when estimating Equation (2) with 50 instead of 4 different FICO buckets. Table A2 provides further results separately for cashback, miles, and points cards. We find a similar pattern across all reward types, with miles cards of low FICO consumers exhibiting the most negative net rewards.

Figure 2: **Coefficient Plot: Net Reward Coefficients For Each Month of 2019**
This figure illustrates the regression coefficients from Equation (2) separately for each month of 2019. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). The dashed black and the solid red, orange, blue, and green lines represent the regression coefficients for all cardholders and for sub-prime, near-prime, prime, and super-prime cardholders, respectively. The shaded areas represent the corresponding 95% confidence intervals.



Robustness. While we focus on the cross-section of March 2019 for most of our paper due to computational constraints, we replicate our baseline results from Columns (3) and (4) in Table 2 separately for each month of 2019. Figure 2 illustrates the respective coefficients for the entire sample (dashed line) and for each of the four FICO buckets (solid lines). Across all months, we find that net rewards for reward cards are on average significantly higher than for similar non-reward cards in the full sample, with the magnitude ranging from $1.9 (in February) to $7.3 (in June). Similarly, net rewards for sub-prime and near-prime cardholders are consistently lower on reward cards than on similar non-reward cards, while for prime and super-prime consumers they are consistently higher. Thus, our results hold for each month of 2019 and are not driven by any sample selection effects that are specific to March.

Next, we provide further robustness checks regarding our regression specification. While our baseline results compare very similar cardholders by using a granular set of fixed effects, our results could still be driven by remaining heterogeneity across cards and cardholders. As shown in Table 1, reward cards tend to have lower APRs and higher credit limits than non-reward cards. Individuals might therefore chose to borrow on reward cards to access more credit at a cheaper price and our results might be driven by such differences in consumer

preferences. To alleviate these concerns, columns (1) and (2) of Table 3 augment our baseline specification with credit limit percentile and APR percentile fixed effects. While the sample size is now substantially smaller, due to the increased number of fixed effects, we obtain significant and qualitatively similar results, albeit smaller in magnitude.[21] In columns (3) and (4), we replicate our baseline specification on the sample used in columns (1) and (2) and find that the change in magnitudes is largely driven by sample selection effects.

Our data set further contains a unique individual identifier within banks which allows us to compare credit card outcomes between reward and non-reward cards within the same cardholder j. Restricting our sample to the set of individuals who own at least one reward card and one non-reward card at the same bank, we can estimate our baseline specification with cardholder fixed effects, thus comparing the outcomes of reward and non-reward cards *within the same individual*. As shown in columns (5) and (6) of Table 3, we obtain quantitatively similar results as in our baseline specification in Table 2. One limitation of our data set is the impossibility to track individuals across banks. Thus, the interpretation of these results is subject to the caveat that individuals might hold additional, unobserved credit cards at other banks. Furthermore, while the within-individual comparison has the advantage of controlling for all unobservable individual heterogeneity (like differences in tastes and preferences), it ignores the potential spillover effects that other (reward or non-reward) credit cards could have on the outcomes of the observed cards.

Aggregate redistribution. Our results show that credit card rewards induce a redistribution from low- to high-FICO consumers. To illustrate the aggregate size, we sum up the net rewards of reward cards with positive and of reward cards with negative net rewards, both across all cardholders and within each FICO bucket. The economic magnitude is substantial. In 2019, cardholders with negative net rewards in aggregate paid \$44.4 billion for the use of reward cards and cardholders with positive net rewards earn \$15.3 billion.[22] Of the \$44.4 billion that are paid by cardholders with negative net rewards, \$11.4 billion come from

[21] To further alleviate the concern that our results are driven by borrowing demand due to lower APRs on reward cards, Table A3 provides further robustness checks with various fixed effect structures that focus on APR percentile fixed effects. Our results are robust to all these alternative specifications.

[22] Table A4 summarizes our aggregate findings where the difference of \$29.1 billion constitutes bank income. As discussed in Section 3.2, our regression sample is smaller than our full sample due to the exclusion of cards in sparsely populated fixed effects cluster. To obtain accurate estimates for the aggregate redistribution, we use the number of cards in the full sample relative to the number of cards in the regression sample as scaling factors, which range from 1.79 in May to 1.87 in July. Note that this still constitutes a lower bound for the aggregate redistribution induced by reward programs since our overall sample covers only about 70% of the U.S. credit card market.

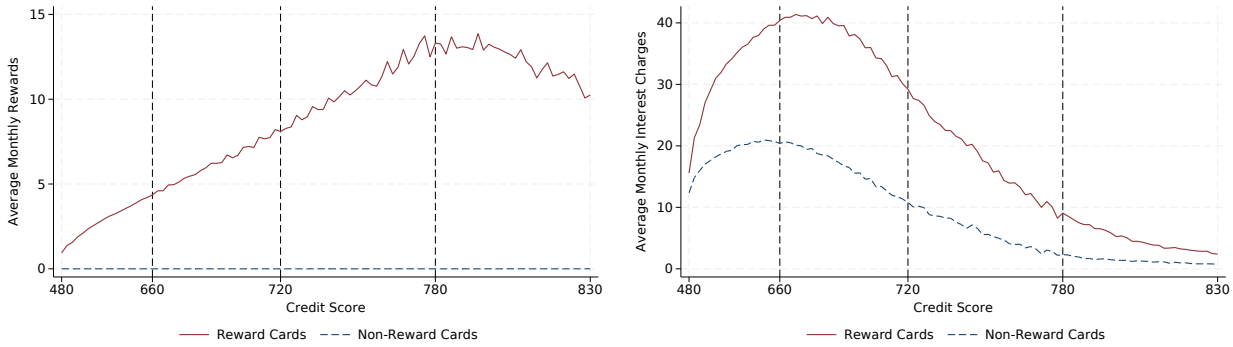
Table 3: **Net Rewards: Robustness Tests**

This table presents robustness checks for the estimation results for differences in net rewards between reward cards and non-reward cards. The outcome variable is the net reward of card i as defined in Equation (1) in Section 3. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. Columns 1 and 2 use our baseline fixed effects structure from Column 3 in Table 2 and additionally include credit limit percentile and APR percentile fixed effects. Columns 3 and 4 estimate our baseline specification from Equation (2) on the sample of columns 1 and 2. Columns 5 and 6 include cardholder fixed effects. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net Rewards					
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	0.62***		1.94***		1.77***	
	(0.15)		(0.51)		(0.37)	
Reward Card × Sub-Prime		-0.49***		-1.02***		-5.53***
		(0.09)		(0.16)		(1.07)
Reward Card × Near-Prime		-0.95***		-1.79***		-8.53***
		(0.35)		(0.53)		(0.96)
Reward Card × Prime		1.20***		2.89***		4.08***
		(0.30)		(0.44)		(0.47)
Reward Card × Super-Prime		2.62***		6.50***		14.09***
		(0.34)		(1.20)		(1.03)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	-	-
FE: Baseline	-	-	Y	Y	-	-
FE: Baseline × Lim × APR	Y	Y	-	-	-	-
FE: Bank × Cardholder	-	-	-	-	Y	Y
Observations	12,381,801				65,513,743	

sub-prime, $17.4 billion from near-prime, $11.5 billion from prime, and only $4.1 billion from super-prime cardholders. Of the $15.3 billion earned by cardholders with positive net rewards, only $0.3 billion go to sub-prime, $1.4 billion to near-prime, $4.5 billion to prime, and $9.0 billion to super-prime cardholders. Thus, while sub-prime and near-prime cardholders are the largest source of funding for credit card rewards, prime and super-prime cardholders are the biggest beneficiaries. Reward credit cards therefore constitute a substantial aggregate transfer from low- to high-FICO score consumers.

Figure 3: **Net Reward Components Across FICO Score Percentiles**
This figure illustrates the dollar magnitude of average rewards (Panel A) and interest charges (Panel B) across the FICO distribution, separately for reward cards (solid red line) and non-reward cards (dashed blue line). For each card type, we plot the average reward and interest charges for 100 equal-sized FICO buckets between 480 and 830. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our baseline sample of 238 million credit cards in March 2019.



(a) Rewards

(b) Interest Charges

4.3 Net Rewards Components

We next examine the three individual components of net rewards: rewards, interest charges, and total fee charges. The differences in net rewards along the FICO distribution suggests that these costs and benefits also vary across FICO scores. Figure 3 illustrates that this is the case. Rewards are increasing in FICO scores (Panel A) and highest for super-prime cardholders, whereas interest charges are hump-shaped in FICO scores (Panel B) and lowest for super-prime cardholders.[23] While interest charges are generally higher for reward cards than for non-reward cards, this difference is largest for near-prime cardholders in the left part of the distribution.

We substantiate this descriptive evidence by estimating Equation (2) with rewards, interest charges, and total fee charges as outcome variables. Results are shown in Table 4. Rewards are on average \$6.4 higher on reward cards than on non-reward cards (column 1) but this difference increases along the FICO distribution, ranging from \$1.8 for sub-prime cardholders to \$9.5 for super-prime cardholders (column 2). High-FICO consumers do not only earn more money in rewards, they also incur lower interest charges. For sub-prime and near-prime cardholders, interest charges are on average \$6.4 and \$10.9 higher on reward cards than on similar non-reward cards, while for super-prime cardholders interest charges

[23] Figure A2 also illustrates total fee charges, which are substantially smaller in magnitude.

are $7.1 lower (column 4). Finally, fee charges are economically less relevant: the difference between reward and non-reward card is less than a US dollar and is quite similar along the FICO distribution (columns 5 and 6). These results show how high-FICO consumers rake in the benefits while avoiding the costs of reward credit cards and therefore profit from usage, while low-FICO consumers incur high costs due to high interest charges.

5 The Reverse Robin Hood Hypothesis

We next investigate whether differences in net rewards across FICO scores are driven by underlying differences in cardholders' income, which would suggest a redistribution from poor to rich consumers. If FICO scores are positively correlated with income and high-income consumers spend more money, then they will earn higher rewards. Indeed, in the financial press, credit card rewards are often framed as a reverse Robin Hood mechanism in which the "poor foot much of the bill for credit card points, miles, and cashback" (Vox, 2023).

Our results, however, show that this explanation is at best incomplete. First, FICO scores and income are only moderately correlated, as also documented in Beer et al. (2018). Figure A5 plots the median FICO score across 100 equal-sized income brackets, alongside the range between the 25^{th} and the 75^{th} percentile (inter-quartile range) and the range between the 10^{th} and the 90^{th} percentile of the FICO distribution within each bracket. While higher income brackets exhibit higher median FICO scores, there is a large overlap, with a non-trivial number of both 'low-income high-FICO' and 'high-income low-FICO' cardholders, as illustrated by the inter-quartile ranges. This allows us to study net rewards across the FICO distribution within different income groups. We split cardholders into terciles of low-income cardholders with an annual income below $44 thousand, middle-income cardholders with an annual income between $44 thousand and $79 thousand, and high-income cardholders with an annual income above $79 thousand.

Panel A of Figure 4 illustrates the magnitude of average net rewards for reward cards across the FICO distribution for the three income groups.[24] All income groups exhibit a pattern similar to what is observed in the whole sample, suggesting that FICO scores still play a key role in shaping the distribution of net rewards, regardless of income. For super-

[24]For ease of exposition, Figure 4 only plots net rewards for reward cards. Panel A of Figure A3 additionally plots net rewards for non-reward cards. Additionally, Panel B of Figure A3 shows the coefficient plot which traces the coefficients δ^F alongside the 95% confidence intervals when estimating Equation (2) with 50 instead of 4 different FICO buckets for the three different income buckets, respectively. Figure A4 further illustrates the magnitude of net rewards across income percentiles, showing that there is no clear pattern in net rewards across the income distribution.

Table 4: **Net Reward Components**

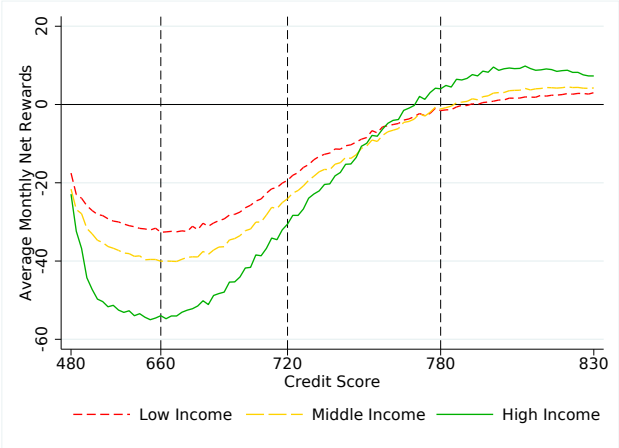
This table presents the estimation results for differences in net reward components between reward cards and non-reward cards from Equation (2) in Section 4.1. The outcome variables are the dollar amount of rewards (columns 1 and 2), the dollar amount of interest charges (column 3 and 4), and the dollar amount of total fee charges (column 5 and 6). The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. All columns employ our baseline fixed effect structure from Column 3 in Table 2. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Rewards		Interest Charges		Total Fee Charges	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	6.38***		2.20***		0.70***	
	(0.35)		(0.18)		(0.08)	
Reward Card × Sub-Prime		1.79***		6.38***		0.78***
		(0.14)		(0.69)		(0.10)
Reward Card × Near-Prime		4.83***		10.86***		0.78***
		(0.27)		(0.75)		(0.12)
Reward Card × Prime		8.39***		0.34		0.77***
		(0.31)		(0.24)		(0.08)
Reward Card × Super-Prime		9.45***		-7.09***		0.50***
		(0.38)		(0.64)		(0.06)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	Y	Y
FE: Baseline	Y	Y	Y	Y	Y	Y
Observations	237,573,278					

prime individuals, the distribution of average net rewards across income groups is consistent with a reverse Robin Hood hypothesis. High-income consumers with high FICO scores benefit the most from reward credit cards compared to mid- and low-income consumers with high FICO scores. At the lower end of the FICO distribution, however, this pattern is reversed. On average, net rewards are far more negative for high-income consumers with low FICO scores than for middle- and low-income consumers with low FICO scores.

Table 5 shows that these patterns hold when including the granular set of fixed effects used in the baseline analysis and controlling for card- and cardholder-specific characteristics. Columns (1), (3), and (5) show that net rewards are higher for reward cards than for non-reward cards in all income groups. While average net rewards are increasing with income,

Figure 4: **Net Rewards Across FICO Score Percentiles by Income Groups**
This figure illustrates the dollar magnitude of average (Panel A) and total (Panel B) net rewards on reward cards across the FICO distribution by income groups. The red line in each panel illustrates the average or total net reward for cardholders with an annual income below $44 thousand, the yellow line for borrowers with an annual income between $44 thousand and $79 thousand, and the green line for borrowers with an annual income above $79 thousand. For each income group, we plot the average (in dollar) or total net reward (in dollar million) for 100 equal-sized FICO buckets between 480 and 830. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our baseline sample of 238 million credit cards in March 2019.



(a) Mean Net Rewards by Income Groups



(b) Sum of Net Rewards by Income Groups

they remain positive also in the bottom tercile of the income distribution ($1.9), inconsistent with the narrative that the poor pay for the positive net rewards of the rich. Instead, columns (2), (4), and (6) show that the relevant redistribution occurs from low- to high-FICO cardholders, regardless of the income level. In fact, sub-prime cardholders in the highest income tercile have more negative net rewards (-$12.7) than sub-prime cardholders in the middle-income (-$4.9) and low-income tercile (-$2.6), respectively. By contrast, prime and super-prime cardholders exhibit positive net rewards across all income groups. High-income super-prime cardholders earn on average $20.1 in net rewards, while middle- and low-income super-prime cardholders earn on average $13.6 and $9.7, respectively.

The combined results in Panel A of Figure 4 and Table 5 show that, on average, high-income consumers with high FICO scores benefit from reward credit cards largely at the

Table 5: **Net Rewards by Income Groups**

This table presents the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section 4.1, estimated separately for three different income groups: low-income cardholders with an annual income below $44 thousand; middle-income cardholders with an annual income between $44-79 thousand; and high-income cardholders with an annual income above $79 thousand. The outcome variable is the net reward of card i as defined in Equation (1) in Section 3. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. All columns employ our baseline fixed effect structure from Column 3 in Table 2. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Lower Income Tercile		Middle Income Tercile		Upper Income Tercile	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	1.86***		2.73***		5.36***	
	(0.20)		(0.28)		(0.61)	
Reward Card × Sub-Prime		-2.56***		-4.88***		-12.75***
		(0.34)		(0.59)		(1.18)
Reward Card × Near-Prime		-2.36***		-5.80***		-13.15***
		(0.45)		(0.58)		(0.77)
Reward Card × Prime		5.93***		6.29***		8.70***
		(0.33)		(0.37)		(0.58)
Reward Card × Super-Prime		9.71***		13.60***		20.10***
		(0.60)		(0.71)		(1.03)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	Y	Y
FE: Baseline	Y	Y	Y	Y	Y	Y
Observations	75,159,536		79,540,729		82,873,013	

expense of high-income consumers with low FICO scores.[25]

These average results, however, are not informative about the aggregate redistribution

[25]Table A5 further substantiates this finding by showing very similar results for the top 10% and 5% of the income distribution, respectively. One caveat is that cardholders infrequently update their income on existing cards. To address the issue of stale and therefore incorrect income data, Table A6 provides a robustness check which focuses on credit cards which were originated within 1 year prior to March 2019. We find that the results are smaller in magnitude–as new cards had less time to accumulate outstanding balances–but qualitiatively similar and statistically significant, despite a considerably smaller sample size.

across income groups, as there are fewer low-FICO cardholders with high than with low income, and vice versa.[26] To illustrate the aggregate redistribution across income groups, Panel B of Figure 4 shows the total sum of net rewards across the FICO distribution for the three income groups. For super-prime cardholders, the distribution of net rewards is again consistent with a reverse Robin Hood mechanism. High-income super-prime cardholders benefit the most from reward programs in the aggregate. At the lower end of the FICO distribution, the aggregate amount of net rewards is of roughly equal magnitude across all income groups. Thus, the presence of a relatively small number of high-income cardholders with low FICO scores makes their aggregate negative net rewards in line with those of lower income cardholders.[27] However, since neither the average nor the aggregate redistribution is primarily driven by income, our overall results are inconsistent with a reverse Robin Hood mechanism.

6 Credit Card Rewards and Financial Sophistication

We next investigate whether our results can be explained by underlying differences in financial sophistication. Financial sophistication refers to the ability of consumers to make informed decisions and avoid mistakes in the use of financial products (Calvet et al., 2009; Lusardi and Mitchell, 2014). Conversely, low financial sophistication is often linked to behavioral biases, such as over-indebtedness (Meier and Sprenger, 2010; Gathergood, 2012) and suboptimal repayments (Kuchler and Pagel, 2021). The financial behavior of consumers is reflected in their FICO scores, which are largely based on an individual's payment history and outstanding debt relative to available credit. Consequently, individuals with higher (lower) FICO scores have been found to incur lower (higher) interest payments, fee payments, and charge-offs (Agarwal et al., 2015). FICO scores thus capture the same type of credit card behavior that is associated with a lack of financial sophistication, namely overindebtedness and suboptimal repayment behavior. Therefore, a large stream of the existing literature uses FICO scores as a measure for financial sophistication (Agarwal et al., 2016; Amromin et al.,

[26] Table A7 illustrates the share of credit cards across FICO and income buckets in our sample. While low-income sub-prime cardholders make up 8.2% of our sample, high-income sub-prime cardholders make up only 3.6%. Conversely, high-income super-prime cardholders make up 14.3% of our sample, but low-income super-prime cardholders make up only 6.7%.

[27] Table A8 summarizes our aggregate findings across FICO and income groups, both in dollar terms (Panel A) and as a percentage share of total rewards (Panel B). We find that low-income sub- and near-prime cardholders account for 20% of all negative net rewards but only for 3% of all positive net rewards. Conversely, high-income super-prime cardholders account for only 5% of all negative net rewards but for 38% of all positive net rewards.

2018; Bhutta et al., 2024; Gibbs et al., 2024).

6.1 Overindebtedness

We first study whether credit card rewards affect consumers' credit card usage behavior and if, consistent with the interpretation of FICO scores as a proxy measure for financial sophistication, this effect is stronger for low-FICO cardholders. While there is anecdotal evidence that reward cards induce higher spending and borrowing, causal identification of such an effect is empirically challenging.[28] The ideal experiment would randomly assign a reward feature to a non-reward card and then track changes in credit card outcomes over time. While this ideal experiment is not feasible, we approximate it by studying the differential spending and borrowing responses of reward and non-reward cards to increases in credit card limits and therefore an increase in available credit (Gross and Souleles, 2002; Aydin, 2022).[29]

We collect all credit cards which received a *bank-initiated* credit limit increase in March 2019, the month of our cross-sectional analysis.[30] We then obtain data on spending, repayments, and unpaid balances for these cards in a 1-year time window around the credit limit increase and compare the outcome changes of reward cards to the outcome changes of non-reward cards in a standard difference-in-differences setting:

$$\Delta \mathrm{Y}_{i(\pm 6m)} = \sum_{F} \left(\delta^{F} \times \text{Reward Card}_i \times D^{F} \right) + \alpha_{z,b} + \sum_{m} X_i^m + \sum_{n} X_j^n + \varepsilon_i \qquad (3)$$

The dependent variable is the change in average spending, repayments, or unpaid balances between the 6-month period before and the 6-month period after the credit limit increase. We calculate credit card outcomes by aggregating over all cards owned by the individual which received a credit limit increase.[31] As in Equation (2), *Reward Card* takes the value 1 for reward cards and 0 for non-reward cards, and D^F is a set of FICO bucket dummy variables

[28] For example, the popular comparison website Finder warns that "the potential for travel perks, cashback and bonus points could cause you to spend more than normal, potentially resulting in high fees and interest on those purchases". Similarly, an article on nasdaq.com cautions against "consistently overspending in the hopes of getting rewards".

[29] The underlying idea is that a *bank-initiated* credit limit increase of, e.g., $1000 on an existing reward (or non-reward) card is economically equivalent to the issuance of a new reward (or non-reward) card with a $1000 limit and without a cardholder request.

[30] Our dataset allows us to distinguish between credit limit increases initiated by the bank and those requested by the cardholder. We focus on the former to rule out anticipated changes in spending and borrowing.

[31] Table A9 provides a robustness check which, for each consumer, only considers the cards with a credit limit increase, finding qualitatively similar results.

for sub-prime cardholders (with a FICO score below 660), near-prime cardholders (600-720), prime cardholders (720-780), and super-prime cardholders (above 780). We include Bank × ZIP code fixed effects, the standard set of card- and cardholder-level control variables, and further income, FICO scores, spending, and payments, all measured by their pre-treatment averages.[32]

Table 6 presents the estimation results of Equation (3) with spending, repayments, and unpaid balances as outcome variables. Across all cardholders in our sample, we find that the spending response to a credit limit increase is higher on reward than on similar non-reward cards (column 1). The difference is economically meaningful and amounts to $80, which corresponds to about 8% of average monthly spending. We also find a differential increase in repayments, albeit smaller in magnitude ($38, column 3). As a result, unpaid balances on reward cards increase compared to similar non-reward cards ($46), suggesting that an increase in credit limits on reward cards induces consumers to incur higher unpaid balances relative to non-reward cards.

As before, these average results mask important differences across the FICO distribution. While credit limit increases on reward cards induce all cardholders to spend more, with the effect being larger for high-FICO consumers (column 2), only prime and super-prime cardholders also increase their repayments by a commensurate magnitude (column 4). In contrast, for low-FICO consumers the increase in payments is substantially smaller in magnitudes. As a result, credit limit increases on reward cards yield a significant increase in unpaid balances for sub-prime ($45.3) and near-prime ($61.0) consumers, while unpaid balances do not change significantly for high-FICO consumers (column 6).[33] These results suggest that credit card rewards induce sub- and near-prime consumers to incur more credit card debt, consistent with the interpretation of FICO scores as a measure for financial sophistication.

6.2 Suboptimal Repayment Behavior

A recent stream of literature further attempts to quantify the financial sophistication of households by measuring the extent to which they make well-defined mistakes in the use of

[32] As our sample is now limited to cards with a credit limit increase in March 2019, we cannot estimate the model with the same set of granular fixed effects used in the baseline analysis, as such a specification would yield a very small and non-representative sample.

[33] The spending and borrowing increase of low FICO consumers could be a rational response to the reward cards' lower interest rates. To alleviate this concern, Table A10 shows that our results are robust to the inclusion of APR percentile fixed effects, thus comparing reward and non-reward cards with very similar interest rates.

Table 6: **Overindebtedness: Difference-in-Differences Analysis**

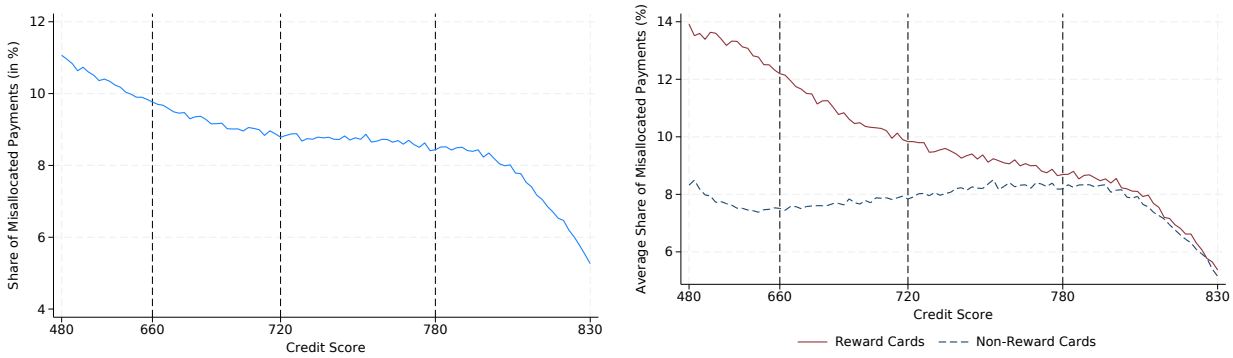
This table presents the estimation results for the difference-in-differences regression in Equation (3) in Section 6.1. We compare changes in credit card outcomes of consumers who received a *bank-initiated* credit limit increase on reward cards to those who received a bank-initiated limit increase on non-reward cards in a time window 6 months before and after the credit limit increase. The outcome variables are changes in spending volumes (columns 1 and 2), credit card payments (columns 3 and 4), and unpaid balances (columns 5 and 6). The analysis considers all cards of consumers who received a bank-initiated credit line increase. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups D: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the FICO score, the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls income, a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, a bankruptcy indicator, and average spending and payments in the pre-treatment period. Borrower income and FICO are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Spending		Δ Payments		Δ Unpaid Balances	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	79.93***		38.38***		46.19***	
	(7.73)		(3.71)		(13.88)	
Reward Card × Sub-Prime		60.85***		11.27***		45.30***
		(6.95)		(3.01)		(13.32)
Reward Card × Near-Prime		67.10***		14.49***		60.97***
		(7.85)		(3.81)		(18.98)
Reward Card × Prime		100.45***		83.96***		32.78*
		(9.53)		(7.15)		(17.55)
Reward Card × Super-Prime		189.76***		171.87***		11.85
		(14.95)		(13.83)		(30.51)
Card Controls (Pre)	Y	Y	Y	Y	Y	Y
Cardholder Controls (Pre)	Y	Y	Y	Y	Y	Y
Income & FICO (Pre)	Y	Y	Y	Y	Y	Y
Spending & Payments (Pre)	Y	Y	Y	Y	Y	Y
FE: Bank × Zip	Y	Y	Y	Y	Y	Y
Observations	953,950					

financial products (Calvet et al., 2009; Jørring, 2024). Specifically, we follow Ponce et al. (2017) and Gathergood et al. (2019) and calculate the share of misallocated repayments for consumers with multiple credit cards at the same bank.[34] This measure can be interpreted

[34]The optimal repayment rule is to first make the minimum payment due on all cards, then pay off in full the card with the highest APR, and subsequently pay off cheaper cards in order of their APRs. The misallocated payment share is the difference between optimal and actual payments as a share of total payments — see Online Appendix (B).

Figure 5: **Share of Misallocated Payments Across FICO Score Percentiles**
This figure illustrates the average percentage share of misallocated payments across the FICO distribution at the borrower level (Panel A) and separately for reward cards (solid red line) and non-reward cards (dashed blue line) (Panel B). In each panel, we plot the average share of misallocated payments for 100 equal-sized FICO buckets between 480 and 830. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our sample of 34 million credit cards of borrowers who hold multiple credit cards at the same bank in March 2019.



(a) Borrower Level

(b) Reward Cards versus Non-Reward Cards

as the share of payments that were incorrectly made on a cheaper card that should have been made on more expensive cards.

We first plot the share of misallocated payments at the borrower level across the FICO distribution, aggregated over both reward cards and non-reward cards. Panel A of Figure 5 shows that misallocated payments are decreasing in FICO scores, consistent with high-FICO consumers being more financially sophisticated. Panel B of Figure 5 further shows that misallocated payments are higher on reward cards, especially for low-FICO consumers. For super-prime cardholders, the misallocated payment share is as low as 6 percent on both reward cards and non-reward cards. Sub-prime cardholders, in contrast, misallocate up to 14 percent of all credit card repayments on reward cards and around 8 percent on non-reward cards.

We next estimate Equation (2) with the share of misallocated payments as the outcome variable. Table 7 presents the results for this analysis when imposing increasingly stricter sample restriction criteria. In the most restrictive sample in columns (5) and (6), we consider cards with different APRs owned by individuals with at least two cards with unpaid balances, who made minimum payments on all cards, and more than the minimum on at least one card. In this sample, we find that the share of misallocated payments is almost 2 percentage points higher on reward than on non-reward cards (column 5). This result is exclusively

Table 7: **Share of Misallocated Payments**

This table presents the estimation results for differences in the share of misallocated payments (as defined in Equation A5 in Online Appendix B) between reward cards and non-reward cards from Equation (2) in Section 4.1. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. We sequentially restrict the sample to cardholders who (i) hold at least two cards with revolving debt at the same bank; (ii) have not fully paid balance on all cards with revolving debt; (iii) made the minimum payment on all cards with revolving debt and more than the minimum on at least one; and (iv) have different APRs on all cards with revolving debt. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Share of Misallocated Payments					
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	1.24***		1.71***		1.74***	
	(0.28)		(0.33)		(0.37)	
Reward Card × Sub-Prime		2.65***		3.74***		4.18***
		(0.20)		(0.25)		(0.30)
Reward Card × Near-Prime		0.76***		1.15***		1.08***
		(0.28)		(0.34)		(0.35)
Reward Card × Prime		0.14		0.35		0.13
		(0.37)		(0.41)		(0.42)
Reward Card × Super-Prime		0.07		0.30		0.12
		(0.41)		(0.44)		(0.47)
Restrictions:						
(i) Two revolving cards	Y	Y	Y	Y	Y	Y
(ii) Balances not fully paid	Y	Y	Y	Y	Y	Y
(iii) Minimum payment	N	N	Y	Y	Y	Y
(iv) Different APRs	N	N	N	N	Y	Y
Card Controls	Y	Y	Y	Y	Y	Y
FE: Cardholder × Bank	Y	Y	Y	Y	Y	Y
Observations	21,288,917		16,136,165		12,858,916	

driven by low-FICO cardholders. While we find a 4.2 percentage point higher share of misallocated payments on reward cards for sub-prime cardholders, there is no significant difference between reward and non-reward cards for prime- and super-prime cardholders. Thus, reward cards do not only induce low-FICO consumers to overborrow, but also to engage in suboptimal repayment behavior. These results also hold true when relaxing some of the sample restrictions (columns 1-4).[35]

Finally, we follow Gathergood et al. (2019) and show that cardholders follow a suboptimal balance-matching heuristic when repaying their credit cards. Rather than optimally allocating repayments across cards based on their APRs, individuals tend to repay their cards

[35]Results are also robust to restricting the sample to individuals with only two cards (Table A11).

Table 8: **Misallocated Payments and Heuristics**

This table compares the actual payment amounts to the theoretical payment amounts based on three different heuristics as discussed in Section 6.2: (i) the optimal repayment rule, (ii) the balance-matching heuristic, and (iii) an equal allocation across all cards (the 1/N heuristic). The table presents the mean shares and correlation coefficients between the different payment amounts, separately for reward cards (columns 1 and 2) and for non-reward cards (columns 3 and 4).

	Payment on Reward Card(s)		Payment on Non-Reward Card(s)	
	Mean	ρ	Mean	ρ
	(1)	(2)	(3)	(4)
Panel A: All Cardholders ($n = 21,288,917$)				
Actual Share of Payment	48.7%		35.9%	
Optimal Share of Payment	47.0%	0.50	37.5%	0.49
Balance Matching Heuristic Share of Payment	47.5%	0.52	37.0%	0.54
1/N Heuristic Share of Payment	42.8%	0.38	41.4%	0.35
Panel B: Sub-prime Cardholders ($n = 7,469,187$)				
Actual Share of Payment	47.0%		38.8%	
Optimal Share of Payment	43.9%	0.39	41.6%	0.43
Balance Matching Heuristic Share of Payment	47.3%	0.47	38.6%	0.49
1/N Heuristic Share of Payment	43.6%	0.36	41.9%	0.42
Panel C: Near-prime Cardholders ($n = 7,482,795$)				
Actual Share of Payment	47.8%		34.6%	
Optimal Share of Payment	46.8%	0.51	35.6%	0.49
Balance Matching Heuristic Share of Payment	47.9%	0.55	34.6%	0.54
1/N Heuristic Share of Payment	41.8%	0.41	40.0%	0.40
Panel D: Prime Cardholders ($n = 4,412,700$)				
Actual Share of Payment	50.8%		34.3%	
Optimal Share of Payment	49.9%	0.55	35.3%	0.51
Balance Matching Heuristic Share of Payment	47.7%	0.53	37.3%	0.51
1/N Heuristic Share of Payment	42.8%	0.39	42.0%	0.32
Panel E: Super-prime Cardholders ($n = 1,924,235$)				
Actual Share of Payment	53.8%		32.9%	
Optimal Share of Payment	52.1%	0.63	34.5%	0.58
Balance Matching Heuristic Share of Payment	46.8%	0.56	39.9%	0.53
1/N Heuristic Share of Payment	43.4%	0.37	43.2%	0.26

proportional to outstanding balances. We calculate the theoretical repayment amount based on three different rules: (i) the optimal repayment rule, (ii) the balance-matching heuristic, and (iii) an equal allocation across all cards (the 1/N heuristic). As shown in Panel A of Table 8, actual payments are most strongly correlated with the balance-matching heuristic, in line with Gathergood et al. (2019). Again, there is substantial heterogeneity across FICO scores. We find that the correlation between actual payments and the balance-matching heuristic is stronger for sub-prime (Panel B) and near-prime (Panel C) cardholders, while prime (Panel D) and super-prime (Panel E) cardholders exhibit repayment behavior most strongly correlated with the optimal allocation rule. Thus, suboptimal repayment behavior tends to be more severe for low-FICO consumers.

Overall, our findings in Section 6 are consistent with the hypothesis that reward cards exploit the over-borrowing and suboptimal repayment behavior of low-FICO consumers and that FICO scores are a reasonable proxy measure for financial sophistication. Our results therefore suggest that credit card reward programs induce a redistribution from naïve to sophisticated consumers. This interpretation of our results warrants some discussion. While we define financial sophistication as the ability of consumers to avoid mistakes in the use of financial products (Calvet et al., 2009), we remain agnostic regarding the source of this ability. A lack of financial sophistication might therefore reflect individuals' unawareness about their time-inconsistent preferences (DellaVigna and Malmendier, 2004), low levels of financial literacy due to low educational attainment (Lusardi and Mitchell, 2014), attentional neglect due to resource scarcity (Shah et al., 2021), or a combination thereof. These factors all yield a higher propensity for individuals to make financial mistakes, but disentangling these factors is beyond the scope of this paper.[36]

7 The Supply Side: Banks' Pricing and Profits

Our analysis so far focuses on the perspective of cardholders. In this section, we turn to the banks' perspective and study their pricing strategies and profits in the credit card market, across card types and the FICO distribution.

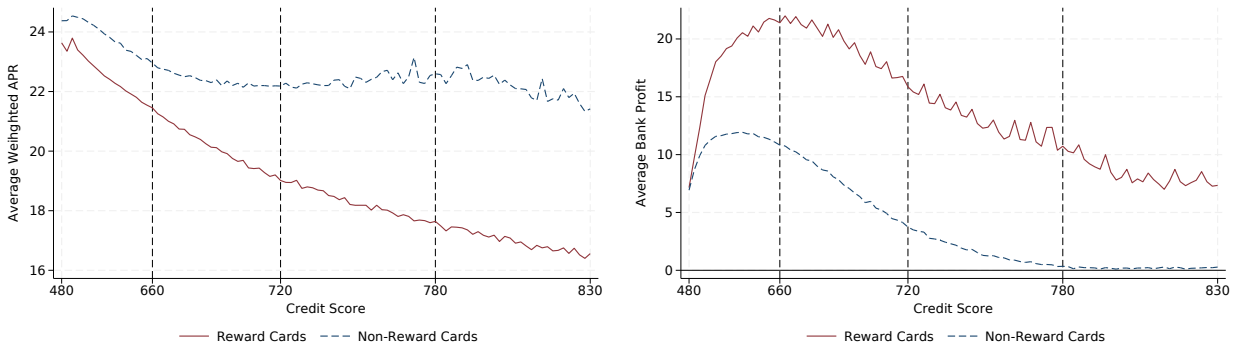
7.1 Pricing

We first study the interest rates offered by banks on reward cards relative to comparable non-reward cards. Panel A of Figure 6 shows that the average annual percentage rate (APR) of interest on reward cards is systematically lower than interest rates on non-reward cards across the entire FICO distribution. The lower APR on reward cards relative to non-reward cards does not reflect zero or low APRs during potential promotional periods, as all credit card accounts in the sample are initiated at least 12 months prior to March 2019.

This pattern is confirmed in our standard regression setting, estimating Equation (2) with

[36] Low FICO scores could arguably also result from adverse life events, such as unexpected unemployment, medical debt, or other negative shocks to the financial well-being of cardholders. In this case, we would overestimate the extent to which our results are driven by financial sophistication. To rule out this possibility, Table A12 provides a robustness check for our main results in Table 2 in which we exclude all cardholders which exhibited a substantial decline in their FICO scores between March 2018 and March 2019. Specifically, we exclude cardholders in the bottom 5% of the distribution of FICO score changes over this period, which corresponds to a decline of larger than 66 points. Our results remain largely unchanged.

Figure 6: **APRs and Bank Profits Across FICO Score Percentiles**
This figure illustrates the average annual percentage rate (APRs) (Panel A) and the average dollar magnitude of bank profits per card (Panel B) across the FICO distribution, separately for reward cards (solid red line) and non-reward cards (dashed blue line). For each card type, we plot the average APR and bank profit for 100 equal-sized FICO buckets between 480 and 830. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our baseline sample of 238 million credit cards in March 2019.



(a) APRs

(b) Bank Profits

APRs as the outcome variable. Columns (1) and (2) of Table 9 present the results. Across all cardholders, APRs on reward cards are on average 1.0 percentage points lower than on comparable non-reward cards. This interest rate differential between reward and non-reward cards is larger for high- than for low-FICO cardholders. For sub-prime cardholders, banks on average offer 0.2 percentage points lower interest rates on reward cards, while for super-prime cardholders the difference is 1.7 percentage points. This evidence indicates that banks incentivize consumers to adopt reward cards by offering better pricing term.

7.2 Bank Profits

At prima facie, offering lower interest rates on reward cards than on comparable non-reward cards may not appear to be a profit-maximizing strategy. However, the evidence on higher interest and fee charges for reward cards (Figure 3) suggests that, despite reward expenses and lower interest rates, these products could generate more profits for banks. To investigate more formally how this pricing strategy translates into profitability, we define a bank's profit on credit card i as:

$$\text{Profit}_i = \text{Interest Charges}_i + \text{Total Fee Charges}_i + \text{Interchange Income}_i \tag{4}$$

$$- \text{Rewards}_i - \text{LLP}_i - \text{Funding Costs}_i - \text{Operational Expenses} \tag{5}$$

Table 9: **Annual Percentage Rates (APR) of Interest and Bank Profits**
This table presents the estimation results for differences in outcomes between reward cards and non-reward cards from Equation (2) in Section 4.1. The outcome variables are the annual percentage rate of interest (APR) (columns 1 and 2) and the dollar amount of bank profits per card as defined in Equation 5 in Section 7.2 (columns 3 and 4). The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. All columns employ our baseline fixed effect structure from Column 3 in Table 2. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	APR		Profit	
	(1)	(2)	(3)	(4)
Reward Card	-0.96***		7.48***	
	(0.19)		(0.71)	
Reward Card × Sub-Prime		-0.20**		2.66*
		(0.09)		(1.41)
Reward Card × Near-Prime		-0.47***		13.10***
		(0.16)		(1.06)
Reward Card × Prime		-1.34***		9.80***
		(0.26)		(0.49)
Reward Card × Super-Prime		-1.65***		3.98***
		(0.27)		(0.43)
Card Controls	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y
FE: Bank × Zip × Income × FICO	Y	Y	Y	Y
Observations	237,573,278			

The variables *Interest Charges*, *Total Fee Charges*, and *Rewards* are defined as in Section 3. Whereas interest and fees represent expenses from the cardholder's perspective, they now represent income from the bank's perspective. Conversely, whereas rewards represent income from the cardholder's perspective, they now represent costs from the bank's perspective. Our analysis of bank profitability also introduces four new terms which are not included in the previous analysis: *Interchange Income*, *LLP*, *Funding Costs*, and *Operational Expenses*. As discussed in Section 2, when consumers pay with their credit card, banks charge an interchange fee from the merchant acquirer, which generally ranges from 1 to 3 percent of the purchase price (GAO, 2009). As interchange fees are generally higher on reward than on non-reward cards (Felt et al., 2023), we assess interchange income at the card level to be

1.25 percent of the purchase volume for non-reward cards and 2.75 percent for reward cards. Furthermore, we follow Adams et al. (2022) and include loan loss provisions (LLP) in the profit definition.[37] The third and fourth term capture banks' funding costs and operational expenses related to outstanding credit card balances.[38]

Panel B of Figure 6 shows that bank profits are hump-shaped in FICO scores and substantially higher on reward than on non-reward cards across the entire FICO distribution. Columns (3) and (4) of Table 9 present the estimation results of Equation (2) with bank profits as the outcome variable. Across all cardholders, bank profits are about \$7.5 higher on reward cards than on comparable non-reward cards. While banks profit from reward cards across the entire FICO distribution, profits are not uniformly distributed, as shown in column (4). We find that bank profits per card are highest for near-prime (\$13.1) and prime (\$9.8) cardholders in the middle of the FICO distribution. For sub-prime cardholders, profits are also higher on rewards cards, but with the differential being smaller in magnitude (\$2.7). For super-prime cardholders, which tend to earn a lot of rewards and also incur low interest payments, bank profits are only \$4.0 higher on reward than on non-reward cards. Thus, from the banks' perspective, near-prime and prime cardholders are the largest source of profits in the market for reward credit cards, even though they profit across the FICO distribution.[39]

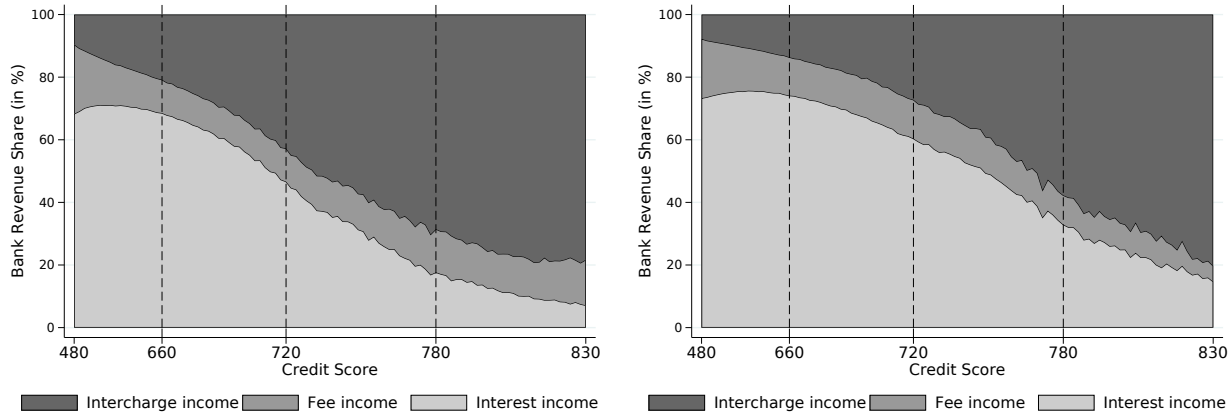
Where do the higher profits on reward cards come from? We document substantial differences regarding banks' sources of credit card revenues across consumer types. Figure 7 illustrates the average revenue share of interest income, fee income, and interchange income as a percentage of total card revenue across the FICO distribution. For low-FICO cardholders, banks' revenues largely stem from interest income. For high-FICO cardholders, on the other hand, banks' revenues largely stem from interchange income. Fee income represents the smallest revenue source of banks. Thus, the interest payments from naïve consumers and the interchange income from sophisticated consumers make reward programs profitable for banks across the FICO distribution.

[37] To calculate LLPs at the card level, we make use of portfolio level data from Schedule D.2 of the Y-14M data and calculate a bank-specific LLP rate defined as LLP expenses over outstanding receivables. We then multiply the LLP rate with outstanding balances at the card level.

[38] We follow Agarwal et al. (2015) and assess funding costs and operational costs at the card level by using Schedule D.2 portfolio level data to calculate bank-specific cost of funds (interest expenses over outstanding receivables) and operational expense rates (operational expenses over outstanding receivables) and then multiplying these rates with outstanding balances at the card level.

[39] This result is consistent with the theoretical framework of Heidhues et al. (2016), who show that credit cards may be profitably sold to naïve consumers even when alternatives such as low-fee debit cards would create more social value.

Figure 7: **Bank Revenue Shares Across FICO Score Percentiles**
This figure illustrates the average bank revenue share across the FICO distribution for 100 equal-sized FICO buckets between 480 and 830, separately for reward cards (Panel A) and non-reward cards (Panel B). For each card type, we plot the share of interchange income (black), fee income (dark gray), and interest income (light gray) as a percentage of total card revenue. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graphs are based on our baseline sample of 238 million credit cards in March 2019.



(a) Reward cards

(b) Non-reward cards

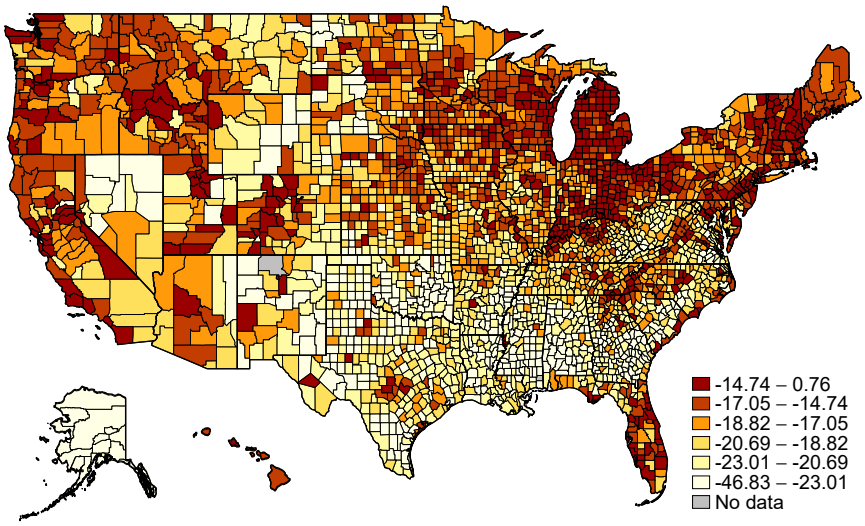
8 The Geography of Net Rewards

Our analysis so far focuses on the redistribution from naïve to sophisticated consumers at the individual level. In this section, we focus on the aggregate implications and analyze the reward-induced redistribution across regions in the United States.

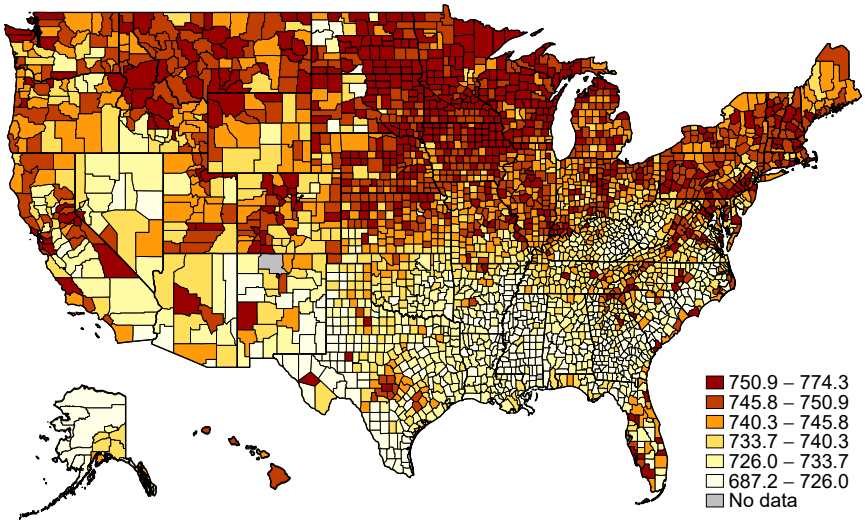
Figure 8 plots the average net reward (Panel A) and the average FICO score (Panel B) across counties. The figure illustrates the high level of spatial correlation between the two variables and confirm, at the aggregate level, the redistribution from naïve to sophisticated consumers in the credit card market. Regions with high average net rewards (the northeast, the north, and the west coast) tend to be regions with high average FICO scores. Conversely, regions with low average negative net rewards (the south) tend to be regions with low average FICO scores.

A relevant concern is whether this redistribution is penalizing areas with specific socio-demographic characteristics, potentially widening existing spatial disparities. To answer this question we regress card-level net rewards on various ZIP code-level characteristics and

Figure 8: **The Geography of Net Rewards and FICO Scores**
This figure illustrates the average dollar amount of net rewards (Panel A) and the average FICO score (Panel B) across counties in the United States. The graph is based on our baseline sample of 238 million credit cards in March 2019.



(a) Average Net Rewards Across Counties



(b) Average FICO Scores Across Counties

estimate the following regression specification:

$$\text{Net Reward}_{i,z} = \sum_k \beta^k X_z^k + \gamma \times \overline{CreditScore}_z + \varepsilon_{i,z} \tag{6}$$

where the outcome variable is the net reward of card i in ZIP code z and where X_z^k are the following ZIP code-level characteristics: i) the percentage of residents with a high school

Table 10: **The Geography of Net Rewards**

This table presents the estimation results for net rewards at the ZIP code-level from Equation (6) in Section 8. The outcome variable is the net reward of card i in ZIP code z and where X_k are the following ZIP code-level characteristics: the percentage of residents with a bachelor's degree as a proxy for education, the median income of individuals in the ZIP code, and the percentage of residents who report their race as Black or African American. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net Rewards					
	(1)	(2)	(3)	(4)	(5)	(6)
Education	0.29***	-0.01				
	(0.02)	(0.02)				
Income			0.21***	0.00		
			(0.02)	(0.02)		
Black Population Share					-0.14***	0.00
					(0.01)	(0.01)
Credit Score		0.19***		0.18***		0.19***
		(0.01)		(0.00)		(0.00)
Observations	237,573,278					

diploma (but no more), as a measure for low educational attainment; ii) the median individual income; and iii) the percentage of residents who report their race as Black or African American. Since these socio-demographic characteristics are likely correlated with average FICO score, we report all coefficients with and without controlling for the average FICO score in ZIP code z.

9 Conclusion

Credit card reward programs provide an ideal laboratory to study the redistribution across consumers in retail financial markets. Using comprehensive and granular data from the Federal Reserve's Y-14M reports, we find that high-FICO consumers benefit from reward programs at the expense of low-FICO consumers and estimate an annual redistribution of of $15.1 billion. This redistribution is driven by both the cost and the benefit margin of reward credit cards. Super-prime and prime consumers spend more money and thus earn higher rewards, but they also pay back their balances in time and thus incur lower interest payments. Conversely, sub-prime and near-prime consumers earn lower rewards and incur higher interest payments due to higher outstanding balances on reward cards.

Notably, our results are not driven by income, as they hold within the sub-samples of low-, middle- and high-income individuals. In particular, high-FICO high-income consumers

benefit the most from reward credit cards, but they do so at the expense of low-FICO high-income consumers. While credit card rewards are often framed as a "reverse Robin Hood" mechanism in which the poor subsidize the rich, our results show that this explanation is at best incomplete.

We rationalize our findings in terms of financial sophistication, meaning that reward cards constitute a redistribution from naïve to sophisticated consumers. We argue that FICO scores can be interpreted as a measure of financial sophistication and, consistent with that, we show that FICO scores are correlated with consumers' financial mistakes. First, we provide quasi-experimental evidence that reward credit cards induce low-FICO consumers to overborrow on their credit cards. Second, we show that FICO scores are strongly correlated with the share of misallocated credit card payments, especially for sub-prime and near-prime cardholders.

We further show that banks incentivize consumers to use reward cards by offering lower interest rates than on comparable non-reward cards. Banks profits from reward cards are highest for near-prime and prime consumers in the middle of the FICO distribution.

We conclude by documenting that the costs and benefits of credit card rewards are unequally distributed across geographies in the United States. Credit card rewards transfer income from less to more educated, from poorer to richer, and from high- to low-minority areas, thereby widening existing spatial disparities.

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Online Appendix

(A) Estimating Monthly Net Rewards

While reward credit cards allow consumers to earn money through the use of credit cards, cardholders may also incur costs in the form of interest payments and fees. To measure the monthly net cash flow on a credit card, we construct the variable *Net Rewards* which subtracts the amount of interest and fees paid on card i in month t from the rewards earned on the card during the same period:

$$\text{Net Rewards}_{i,t} = \text{Rewards}_{i,t} - \text{Interest Paid}_{i,t} - \text{Total Fees}_{i,t} \tag{A1}$$

In our dataset, we directly observe the dollar amounts of *Interest Paid* and *Total Fees*. However, we do not observe the amount of monthly rewards, but only the accumulated rewards as of the reporting month, net of redeemed rewards, that is:

$$\text{Cumulative Rewards}_{i,t} = \text{Cumulative Rewards}_{i,t-1} + \text{Rewards}_{i,t} - \text{Redemptions}_{i,t} \tag{A2}$$

We have data on the stocks *Cumulative Rewards*, but not on the flows *Rewards* and on *Redemptions*. To calculate the monthly net rewards in Equation (1), we estimate the monthly variable *Rewards*. First, we estimate the effective reward rate of card i by dividing the month-to-month change in cumulative rewards by the purchase volume of card i during the given month:

$$\text{Card-Specific Reward Rate}_{i,t} = \frac{\Delta\text{Cumulative Rewards}_{i,t}}{\text{Purchase Volume}_{i,t}} \tag{A3}$$

This estimated reward rate is correct if redeemed rewards in month t are zero. For example, if cumulative rewards on card i increase by 12 dollars in month t and if the card exhibits a purchase volume of \$1000 during the same month, then the estimated effective reward rate equals 1.2 percent. If, however, the cardholder redeems rewards during the month, then this will underestimate the card-specific reward rate. In the case when all rewards are (automatically) redeemed in month t, we would estimate a card-specific reward rate of zero.

To filter out these card-specific idiosyncrasies in redemption behavior, we estimate reward rates at the individual credit card product-level. To this end, we cluster all cards in our sample into groups based on the following variables: bank, credit card type, product type,

card network, reward type, fee type, and fee level.[40] Within each cluster, we calculate the median reward rate using only cards with a positive change in cumulative rewards, that is cards for which $\Delta \textit{Cumulative Rewards}_{i,t} > 0$. We then use the estimated reward rate to calculate the monthly rewards of card i in month t as:

$$\text{Rewards}_{i,t} = \text{Estimated Reward Rate}_{i,t} \times \text{Purchase Volume}_{i,t} \tag{A4}$$

In the raw sample, this methodology yields an average monthly reward of \$13.34 per reward card, which implies an extrapolated average annual reward of \$160.08. This figure is very close to the \$167 in annual rewards per account reported in CFPB (2019), thereby confirming the validity of our approach.

Furthermore, we calculate the variable *Total Fees* as the sum of late, over limit, non-sufficient funds (NSF), cash advance, debt suspension, balance transfer, other, and monthly fees. Combining the data on total fees and interest paid with the estimated amount of monthly rewards from Equation (A4) allows us to calculate the monthly net rewards of card i in month t as defined in Equation (1).

[40] This procedure yields 380 individual credit card product clusters. Table A13 describes all the variables used in the calculation of the variable *Net Rewards*.

(B) Share of Misallocated Payments

This appendix describes the calculation of the share of misallocated payments, following Ponce et al. (2017) and Gathergood et al. (2019). Given the amount of total funds used to pay off credit cards, the optimal, interest-cost-minimizing repayment rule is as follows. First, make the minimum payments due on all cards. Second, pay off in full the card with the highest interest rate. Third, subsequently allocate further repayments to cheaper cards ranked in order of their interest rates. Based on this rule, we calculate the misallocated payment (MP) share for borrower b on card i as the minimum between zero (if the actual payment is equal or lower than the optimal one) and the difference between the optimal payment amount (OPA) and the actual payment amount (APA) scaled by the total payment amount:

$$\text{MP Share} = \begin{cases} \frac{\text{Actual Payment Amount}_{i,b} - \text{Optimal Payment Amount}_{i,b}}{\text{Total Payment Amount}_{i,b}} & \text{if} \quad \text{APA}_{i,b} > \text{OPA}_{i,b} \\ 0 & \text{if} \quad \text{APA}_{i,b} \leq \text{OPA}_{i,b} \end{cases} \tag{A5}$$

This measure can be interpreted as the share of payments that were incorrectly made on a cheaper card that should have been made on more expensive cards. Figure 5 illustrates the share of misallocated payments across the FICO distribution. The misallocated payment share is strongly decreasing in FICO scores. While low-FICO consumers misallocate more than 6 percent of all credit card repayments, the misallocated payment share is less than 2 percent for high-FICO consumers.

(C) Additional Figures

Figure A1: **Coefficient Plot: Net Rewards Across the FICO Distribution**
This figure illustrates the differential dollar magnitude of average net rewards between reward cards and non-reward cards across the FICO distribution. The figure plots the coefficients δ^F alongside the 95% confidence intervals when estimating Equation (2) with 50 instead of 4 different FICO buckets. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our baseline sample of 238 million credit cards in March 2019.

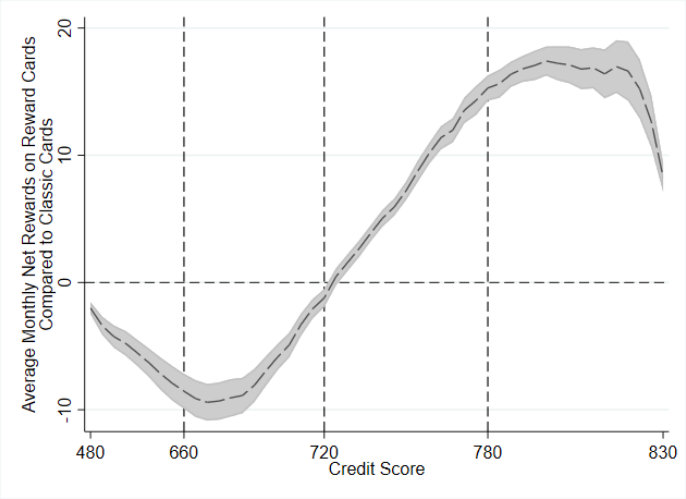


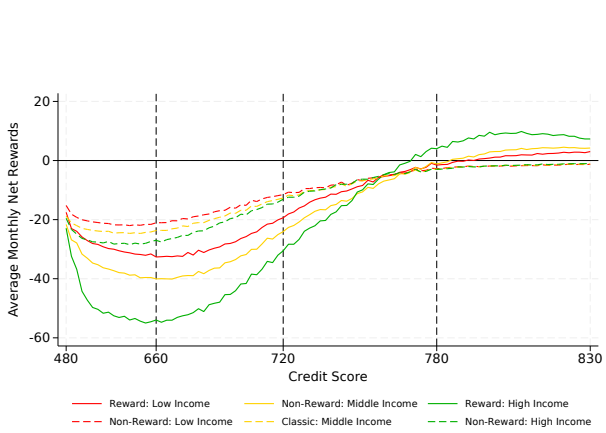
Figure A2: **Fee Charges Across FICO Score Percentiles**

This figure illustrates the dollar magnitude of average fee charges across the FICO distribution, separately for reward cards (solid red line) and non-reward cards (dashed blue line). For each card type, we plot the average fee charge for 100 equal-sized FICO buckets between 480 and 830. The dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our baseline sample of 238 million credit cards in March 2019.

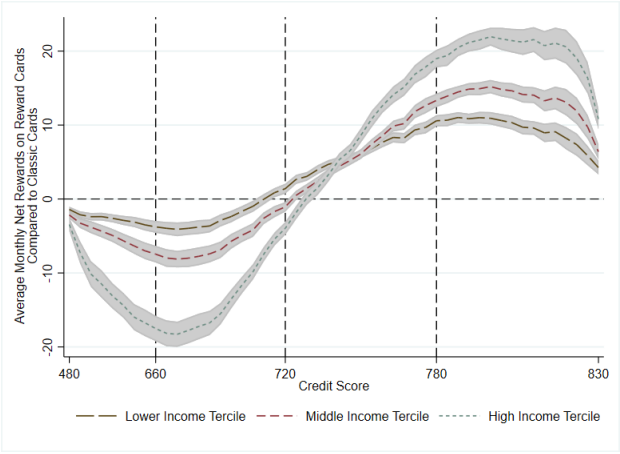


Figure A3: **Net Rewards Across the FICO Distribution by Income**

Panel A plots the dollar magnitude of average net rewards across the FICO distribution, separately for reward cards (solid lines) and non-reward cards (dashed lines), and for three different income groups (below \$44 thousand, \$44 thousand and \$79 thousand, and above \$79 thousand). Panel B plots the coefficients δ^F alongside the 95% confidence intervals when estimating Equation (2) with 50 instead of 4 different FICO buckets separetely for the same three different income buckets. In both panels, the dashed vertical lines mark FICO scores of 660, 720, and 780, our cut-off scores for near-prime, prime, and super-prime cardholders, respectively. The graph is based on our baseline sample of 238 million credit cards in March 2019.



(a) Reward Cards versus Non-reward Cards



(b) Coefficient Plot

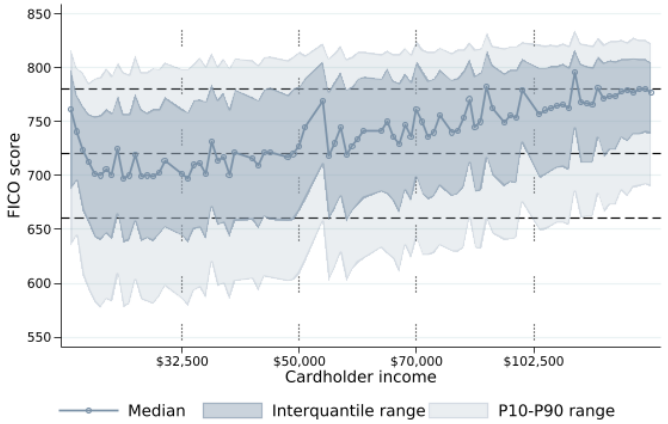
Figure A4: **Net Rewards Across Income Percentiles**

This figure illustrates the dollar magnitude of average net rewards across the income distribution, separately for reward cards (solid red line) and non-reward cards (dashed blue line). For each card type, we plot the average net reward for 100 equal-sized income buckets between $3,000 and $400,000. The dashed vertical lines mark income levels of $44,000 and $79,000, denoting the tercile values in our dataset. The graph is based on our baseline sample of 238 million credit cards in March 2019.



Figure A5: **FICO Scores Across the Income Distribution**

This figure illustrates the distribution of FICO scores across income percentiles. The blue line illustrates the median FICO score within each of 100 equal-sized income buckets. The dark blue and the light blue shaded areas illustrate the corresponding range between the 25^{th} and the 75^{th} percentile of the FICO distribution (inter-quartile range) and the range between the 10^{th} and the 90^{th} percentile of the FICO distribution. The graph is based on our baseline sample of 238 million credit cards in March 2019.



(D) Additional Tables

Table A1: **Robustness Check: Drop FE Cluster With Less Than 5 Cards**
This table presents a robustness check for the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section IV.A, where the outcome variable is the net reward of card i as defined in Equation (1) in Section III. The robustness check drops all Bank x ZIP x FICO x Income fixed effects cluster with less than 5 cards. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net Rewards			
	(1)	(2)	(3)	(4)
Reward Card	3.90***	3.97***	3.78***	
	(0.31)	(0.44)	(0.43)	
Reward Card × Sub-Prime				-5.56***
				(0.85)
Reward Card × Near-Prime				-8.65***
				(0.73)
Reward Card × Prime				7.88***
				(0.43)
Reward Card × Super-Prime				17.06***
				(0.97)
Card Controls	Y	Y	Y	Y
Cardholder 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	81,795,210			

Table A2: **Net Rewards by Type of Reward Card**

This table presents the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section 4.1. We report results separately for the three types of reward cards i.e., miles, cashback, and points. The variable *Reward Card* takes on the value of 1 if card i is a reward card of a given type, and 0 if it is a non-reward card. Cards are clustered in the following FICO score groups D: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Miles Cards		Cashback Cards		Points Cards	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	-4.52***		7.25***		1.57***	
	(1.30)		(0.73)		(0.270)	
Reward Card × Sub-Prime		-26.84***		-2.57***		-6.42***
		(2.30)		(0.47)		(0.46)
Reward Card × Near-Prime		-23.63***		-2.07***		-8.03***
		(2.85)		(0.49)		(0.64)
Reward Card × Prime		0.47		12.41***		4.10***
		(1.41)		(0.70)		(0.31)
Reward Card × Super-Prime		12.62***		22.48***		10.04***
		(1.09)		(1.30)		(0.47)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	Y	Y
FE: Baseline	Y	Y	Y	Y	Y	Y
Observations	113,283,147		153,206,808		158,481,157	

Table A3: **Net Rewards: Robustness Tests: APR Fixed Effects**

This table presents a robustness check for the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section IV.A, where the outcome variable is the net reward of card i as defined in Equation (1) in Section III. These robustness checks include various fixed effect structures that include APR percentile fixed effects. Columns 1 and 2 additionally include Bank × ZIP × APR percentile fixed effects; Columns 3 and 4 include Bank × ZIP × FICO percentile × APR percentile fixed effects; and Columns 5 and 6 include Bank × ZIP × Income percentile × APR percentile fixed effects. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net Rewards					
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	4.80***		1.60***		3.73***	
	(0.17)		(0.17)		(0.23)	
Reward Card × Sub-Prime		-14.87***		-3.50***		-15.14***
		(1.09)		(0.49)		(1.37)
Reward Card × Near-Prime		-12.20***		-3.72***		-12.13***
		(0.89)		(0.61)		(1.06)
Reward Card × Prime		12.37***		5.35***		12.38***
		(0.79)		(0.29)		(0.97)
Reward Card × Super-Prime		28.42***		9.28***		26.87***
		(0.86)		(0.29)		(1.09)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	-	-
FE: Bank × Zip × APR	Y	Y	-	-	-	-
FE: Bank × Zip × FICO × APR	-	-	Y	Y	-	-
FE: Bank × Zip × Income × APR	-	-	-	-	Y	Y
Observations	235,797,417		186,888,061		191,392,602	

Table A4: **Aggregate Net Rewards**

This table presents the aggregate sum of net rewards (in USD billion) for reward cards with negative (column 1) and positive (column 2) net rewards, both for the entire sample (first row) and across different FICO buckets (second to last row). In the second to last row, cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780).

	Negative Rewards (1)	Positive Rewards (2)	Δ (3)
All Reward Cards	-44.4	15.3	-29.1
Sub-Prime	-11.4	0.3	-11.0
Near-Prime	-17.4	1.4	-16.0
Prime	-11.5	4.5	-6.9
Super-Prime	-4.1	9.0	4.9

Table A5: **Net Rewards by Income Groups—Top Income Distribution**

This table presents a robustness check for the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section 4.1. We report results separately for two different annual income groups: cardholders with an annual income in the Top 10% of the income distribution (columns 1 and 2) and cardholders with an annual income in the Top 5% of the income distribution (columns 3 and 4). The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups D: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Top 10% of Income Distribution		Top 5% of Income Distribution	
	(1)	(2)	(3)	(4)
Reward Card	6.96***		7.70***	
	(0.86)		(0.96)	
Reward Card × Sub-Prime		-21.97***		-25.61***
		(1.50)		(1.72)
Reward Card × Near-Prime		-18.35***		-19.43***
		(1.00)		(1.15)
Reward Card × Prime		10.65***		11.77***
		(0.76)		(0.86)
Reward Card × Super-Prime		22.33***		22.24***
		(1.14)		(1.16)
Card Controls	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y
FE: Bank × Zip × Income × FICO	Y	Y	Y	Y
Observations	26,600,689	26,600,689	14,754,880	14,754,880

Table A6: **Net Rewards by Income Groups: Robustness Check: Young Cards < 1 Year** This table presents a robustness check for the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section 4.1, estimated separately for three different income groups: low-income cardholders with an annual income below $44 thousand; middle-income cardholders with an annual income between $44-79 thousand; and high-income cardholders with an annual income above $79 thousand. This robustness check only considers cards which were originated within 1 year prior to March 2019. The outcome variable is the net reward of card i as defined in Equation (1) in Section 3. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Lower Income Tercile		Middle Income Tercile		Upper Income Tercile	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	0.93**		0.92***		1.99***	
	(0.37)		(0.35)		(0.48)	
Reward Card × Sub-Prime		-1.33***		-3.51***		-10.42***
		(0.46)		(0.75)		(0.90)
Reward Card × Near-Prime		0.08		-2.77***		-8.11***
		(0.62)		(0.54)		(0.60)
Reward Card × Prime		4.25***		4.61***		4.92***
		(0.39)		(0.25)		(0.40)
Reward Card × Super-Prime		6.28***		8.61***		11.68***
		(0.35)		(0.33)		(0.41)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	Y	Y
FE: Bank × Zip × Income × FICO	Y	Y	Y	Y	Y	Y
Observations	1,297,933		1,517,390		1,618,324	

Table A7: **Share of Credit Cards Across the FICO and Income Distribution**
This table presents the share of credit cards across the FICO and income distribution. Cards are clustered in the following FICO score groups D: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Furthermore, cards are clustered in the following annual income groups: low (below $44,000), middle ($44-79,000), high (above $79,000). The table is based on our sample of 238 million credit cards in March 2019.

	Income Distributionn:			Sum
	Lower Tercile	Middle Tercile	Upper Tercile	
	(1)	(2)	(3)	(4)
Sub-Prime	8.2%	6.3%	3.6%	18.1%
Near-Prime	8.0%	7.9%	6.6%	22.5%
Prime	8.6%	9.3%	10.5%	28.4%
Super-Prime	6.7%	10.1%	14.3%	31.1%
Sum	31.4%	33.6%	35.0%	100.0%

Table A8: **Aggregate Net Rewards Across the FICO and Income Distribution**
This table presents the aggregate sum of net rewards in USD million (Panel A) and in percent (Panel B) for reward cards with negative and positive net rewards. The table presents numbers both for the entire sample (last row within each panel) and across different FICO buckets (first to fourth row within each panel), and separately for three different annual income groups: low (below $44,000), middle ($44-79,000), high (above $79,000). Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Each cell in Panel B represents the share of positive (negative) net rewards in Panel A relative to the corresponding total sum of positive (negative) net rewards in Table A4. For example, the $1.1 billion positive net rewards for super-prime cardholders in the lower tercile of the income distribution represent 7% of the $15.3 billion positive net rewards shown in Table A4.

	Lower Income Tercile		Middle Income Tercile		Upper Income Tercile	
	Net Rewards		Net Rewards		Net Rewards	
	Negative (1)	Positive (2)	Negative (3)	Positive (4)	Negative (5)	Positive (6)
Panel A. In $b						
Sub-Prime	-4.1	0.1	-4.1	0.1	-3.2	0.1
Near-Prime	-5.0	0.3	-6.1	0.4	-6.4	0.7
Prime	-2.9	0.8	-3.8	1.2	-4.8	2.6
Super-Prime	-0.8	1.1	-1.3	2.2	-2.0	5.7
All Reward Cards	-12.8	2.2	-15.2	3.9	-16.4	9.1
Panel B. In %						
Sub-Prime	9	1	9	1	7	1
Near-Prime	11	2	14	3	14	4
Prime	7	5	8	8	11	17
Super-Prime	2	7	3	14	5	38
All Reward Cards	29	15	34	26	37	60

Table A9: **Overindebtedness: Difference-in-differences Analysis, Excluding Cards without a Bank-initiated Credit Line Increase**

This table presents a robustness check for the estimation results for the difference-in-differences regression in Equation (3) in Section 6.1. This robustness check considers only cards with a bank-initiated credit line increase, rather than aggregating across all cards of consumers who received a bank-initiated credit limit increase. We compare changes in credit card outcomes of consumers who received a *bank-initiated* credit limit increase on reward cards to those who received a limit increase on non-reward cards in a time window 6 months before and after the credit limit increase. The outcome variables are changes in spending volumes (columns 1 and 2), credit card payments (columns 3 and 4), and unpaid balances (columns 5 and 6). The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups D: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the FICO score, the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls income, a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, a bankruptcy indicator, and average spending and payments in the pre-treatment period. Borrower income and FICO are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Spending		Δ Payments		Δ Unpaid Balances	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	75.21***		43.76***		48.28***	
	(6.70)		(3.61)		(11.70)	
Reward Card × Sub-Prime		57.21***		18.83***		46.95***
		(6.27)		(2.82)		(12.13)
Reward Card × Near-Prime		62.65***		21.26***		68.61***
		(6.86)		(3.47)		(16.35)
Reward Card × Prime		89.06***		77.15***		37.70***
		(8.10)		(5.73)		(13.88)
Reward Card × Super-Prime		169.17***		156.26***		-12.77
		(13.02)		(11.72)		(26.40)
Card Controls (Pre)	Y	Y	Y	Y	Y	Y
Cardholder Controls (Pre)	Y	Y	Y	Y	Y	Y
Income & FICO (Pre)	Y	Y	Y	Y	Y	Y
Spending & Payments (Pre)	Y	Y	Y	Y	Y	Y
FE: Bank × Zip	Y	Y	Y	Y	Y	Y
Observations	953,950					

Table A10: **Overindebtedness: DID Robustness Check: APR Fixed Effects**
This table presents a robustness check for the estimation results for the difference-in-differences regression in Equation (3) in Section 6.1. This robustness check includes Bank × ZIP × APR percentile fixed effects. We compare changes in credit card outcomes of consumers who received a *bank-initiated* credit limit increase on reward cards to those who received a limit increase on non-reward cards in a time window 6 months before and after the credit limit increase. The outcome variables are changes in spending volumes (columns 1 and 2), credit card payments (columns 3 and 4), and unpaid balances (columns 5 and 6). The analysis considers all cards of consumers who received a bank-initiated credit line increase. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups D: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the FICO score, the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls income, a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, a bankruptcy indicator, and average spending and payments in the pre-treatment period. Borrower income and FICO are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ Spending		Δ Payments		Δ Unpaid Balances	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	55.46***		36.56***		41.78*	
	(8.47)		(5.52)		(21.80)	
Reward Card × Sub-Prime		47.11***		21.46***		41.89**
		(9.07)		(4.77)		(20.99)
Reward Card × Near-Prime		51.85***		23.87***		59.60**
		(8.35)		(6.03)		(26.12)
Reward Card × Prime		70.43***		75.91***		18.37*
		(10.12)		(10.78)		(27.22)
Reward Card × Super-Prime		98.14***		114.85***		-5.30
		(15.71)		(16.25)		(37.14)
Card Controls (Pre)	Y	Y	Y	Y	Y	Y
Cardholder Controls (Pre)	Y	Y	Y	Y	Y	Y
Income & FICO (Pre)	Y	Y	Y	Y	Y	Y
Spending & Payments (Pre)	Y	Y	Y	Y	Y	Y
FE: Bank × Zip × APR	Y	Y	Y	Y	Y	Y
Observations	622,714					

Table A11: **Share of Misallocated Payments—Two-card Sample**

This table presents a robustness check for the estimation results for differences in the share of misallocated payments (as defined in Equation A5 in Online Appendix B) between reward cards and non-reward cards from Equation (2) in Section 4.1. This robustness check considers only individuals with two credit cards. The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Share of Misallocated Payments					
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	1.15***		1.64***		1.74***	
	(0.34)		(0.41)		(0.46)	
Reward Card × Sub-Prime		2.96***		4.11***		4.60***
		(0.28)		(0.31)		(0.38)
Reward Card × Near-Prime		0.40		0.79**		0.83**
		(0.29)		(0.34)		(0.39)
Reward Card × Prime		-0.34		-0.12		-0.22
		(0.38)		(0.43)		(0.47)
Reward Card × Super-Prime		-0.18		0.10		0.00
		(0.50)		(0.55)		(0.59)
Restrictions:						
(i) Two revolving cards	Y	Y	Y	Y	Y	Y
(ii) Balances not fully paid	Y	Y	Y	Y	Y	Y
(iii) Minimum payment	N	N	Y	Y	Y	Y
(iv) Different APRs	N	N	N	N	Y	Y
Card Controls	Y	Y	Y	Y	Y	Y
FE: Cardholders × Bank	Y	Y	Y	Y	Y	Y
Observations	13,080,528	13,080,528	9,909,754	9,909,754	8,862,432	8,862,432

Table A12: **Robustness Check: Drop cards with Large FICO Decreases**

This table presents a robustness check for the estimation results for differences in net rewards between reward cards and non-reward cards from Equation (2) in Section IV.A, where the outcome variable is the net reward of card i as defined in Equation (1) in Section III. The robustness check drops all cards with a large negative change in FICO scores of more than -66 points between March 2018 and March 2019 (5^{th} percentile of the distribution of changes in FICO scores over this time horizon). The variable *Reward Card* takes on the value of 1 if card i is a reward card, and 0 otherwise. Cards are clustered in the following FICO score groups: sub-prime (below 660), near-prime (660-720), prime (720-780), and super-prime (above 780). Card controls include the credit limit, the amount past due, the card age, a joint account indicator, a fraud flag indicator, and a workout program indicator. Cardholder controls a deposit relationship indicator, a lending relationship indicator, the number of cards held by the cardholder at the same bank, and a bankruptcy indicator. Borrower income and FICO scores are defined as of March 2018 i.e., one year prior to the outcome variable. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net Rewards			
	(1)	(2)	(3)	(4)
Reward Card	4.91***	4.18***	3.76***	
	(0.29)	(0.39)	(0.39)	
Reward Card × Sub-Prime				-5.44***
				(0.68)
Reward Card × Near-Prime				-6.80***
				(0.69)
Reward Card × Prime				7.51***
				(0.44)
Reward Card × Super-Prime				16.01***
				(0.92)
Card Controls	Y	Y	Y	Y
Cardholder 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	225,717,251			

Table A13: **Credit Card Categories**

This table reports the detailed categories used for credit card clustering at the individual product level in the calculation of net rewards in Section 3.1. This procedure yields 380 individual credit card product cluster.

Variable	Categories
Bank	19 banks
Credit Card Type	General Purpose Private Label
Product Type	Co-brand Oil and Gas Co-Brand Affinity Student Other
Network Type	Visa MasterCard American Express Discover Other
Reward Type	Cash Miles Other None
Fee Type	No fee Annual fee Monthly fee
Annualized Fee Amount	0 dollar 0-60 dollar 60-120 dollar 120+ dollar