Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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

Sumit Agarwal, Andrea Presbitero, André F. Silva, Carlo Wix

2023-007

Please cite this paper as:
Agarwal, Sumit, Andrea Presbitero, André F. Silva, and Carlo Wix (2023). "Who Pays For Your Rewards? Redistribution in the Credit Card Market," Finance and Economics Discussion Series 2023-007. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2023.007.

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

Sumit Agarwal Andrea F. Presbitero André F. Silva Carlo Wix*

December 2022

Abstract

We study credit card rewards as an ideal laboratory to quantify redistribution between consumers in retail financial markets. Comparing cards with and without rewards, we find that, regardless of income, sophisticated individuals profit from reward credit cards at the expense of naïve consumers. To probe the underlying mechanisms, we exploit bank-initiated account limit increases at the card level and show that reward cards induce more spending, leaving naïve consumers with higher unpaid balances. Naïve consumers also follow a sub-optimal balance-matching heuristic when repaying their credit cards, incurring higher costs. Banks incentivize the use of reward cards by offering lower interest rates than on comparable cards without rewards. We estimate an aggregate annual redistribution of $15 billion from less to more educated, poorer to richer, and high to low minority areas, widening existing disparities.

Keywords: household finance; credit cards; financial sophistication; rewards

JEL Classification: G21; G40; G51; G53

*Authors' contacts: Sumit Agarwal, National University of Singapore, e-mail: ushakri@yahoo.com; Andrea F. Presbitero, International Monetary Fund and CEPR, e-mail: apresbitero@imf.org; André F. Silva, Federal Reserve Board, e-mail: andre.f.silva@frb.gov; Carlo Wix, Federal Reserve Board, e-mail: carlo.e.wix@frb.gov. We thank our discussants Jared DeLisle, Yaron Levi, Hugo Marin, Paolina Medina, Luciana Orozco, Stephen Shore, and Francesc Rodriguez Tous for helpful comments and suggestions. We are also grateful to Allen Berger, Vitaly Bord, Hans Degryse, Chen Lian, Thomas Mosk, Lakshmi Naaraayanan, Daniel Paravisini, Matthias Rodemeier, Annette Vissing-Jørgensen, Michael Weber, and participants at several conferences and seminars for their valuable suggestions. The views expressed in this paper solely reflect those of the authors and not necessarily those of the Federal Reserve Board or the Federal Reserve System, and neither should be attributed to the International Monetary Fund, its Executive Board, or its management. First version: June 2022.

I. Introduction

Consumers lacking financial sophistication often make costly mistakes (e.g., Campbell, 2006; Gomes, Haliassos, and Ramadorai, 2021). In the consumer credit card market, such behavior can entail overindebtedness (Gross and Souleles, 2002; Heidhues and Kőszegi, 2010) and sub-optimal repayments (Ponce, Seira, and Zamarripa, 2017; Gathergood, Mahoney, Stewart, and Weber, 2019). Banks, in response, can design financial products to exploit these mistakes, combining salient benefits with shrouded payments (DellaVigna and Malmendier, 2004; Heidhues and Kőszegi, 2017). Naïve consumers might underestimate these payments and incur costs from usage. Sophisticated consumers, in contrast, might rake in the benefits while avoiding the payments and thus profit from usage. Such products can therefore generate an implicit redistribution from naïve to sophisticated consumers (Gabaix and Laibson, 2006) and thereby contribute to inequality (Campbell, 2016; Lusardi, Michaud, and Mitchell, 2017).

Despite these theoretical predictions, empirically quantifying the extent of such redistribution is challenging. First, for many financial products such as mortgages, optimal behavior depends on consumers' risk aversion, economic expectations, and other hard-to-measure variables (Campbell and Cocco, 2003; Fisher, Gavazza, Liu, Ramadorai, and Tripathy, 2021; Guiso, Pozzi, Tsoy, Gambacorta, and Mistrulli, 2021). To determine what constitutes biased behavior is therefore not straightforward. Second, linking redistribution to individual characteristics requires detailed individual-level data on the costs and benefits of using a financial product, whereas the latter in particular are often unobservable or at least difficult to quantify.

In this paper, we use credit card rewards as an ideal laboratory to study such redistribution between consumers in retail financial markets. Reward credit cards—which offer points, miles, or cash back to cardholders for every dollar spent—are a ubiquitous feature in Anglo-Saxon consumer credit card markets and are also gaining market share in other countries. In 2019, reward credit cards accounted for 60 percent of all new credit card originations in the United States (CFPB, 2019), with the largest U.S. banks paying $35 billion in rewards. We use comprehensive credit card data from the Federal Reserve Board's Y-14M reports which encompass the near-universe of accounts in the U.S. This data set contains detailed monthly account-level information and is therefore uniquely suited to study redistribution between different consumers. It allow us to compute a cardholder's monthly net reward, defined as the dollar value received in rewards minus interest and fee payments, which captures both the benefits and the costs of credit card usage.

We start our empirical analysis by investigating whether reward credit cards induce redistribution between consumers across the FICO score distribution. To this end, we compare the outcomes of reward cards to those of similar classic 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.[1] 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 classic 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 on average $9.5 in rewards and pay $7.1 less in interest on reward cards than on classic cards. In contrast, sub-prime consumers earn only $1.8 in rewards but pay $6.4 more in interest. Thus, high-FICO cardholders on average earn money with the use of reward cards while low-FICO cardholders on average lose money. In aggregate terms, we find an annualized redistribution of $15.1 billion induced by credit card rewards.

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,

[1]We adopt the following terminology: "Reward cards" are credit cards that earn either cash back, miles, or points; "classic cards" are credit cards that are do not earn any form of rewards.

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 only moderately correlated, as documented in Beer, Ionescu, and Li (2018), we can disentangle these two margins. We find a redistribution from low- to high-FICO consumers regardless of income. While super-prime high-income consumers benefit the most from reward credit cards ($20.1 in net rewards relative to classic cards), high-income consumers with sub-prime FICO scores on average pay the most (-$12.8). Meanwhile, super-prime low-income consumers benefit less ($9.7), but sub-prime low-income consumers also pay less (-$2.6). Thus, high-income consumers with high FICO scores benefit from reward credit cards largely at the expense of high-income consumers with low FICO scores.

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 capture the same type of credit card behavior that is associated with a lack of financial sophistication i.e., overindebtedness and sub-optimal repayment behavior. FICO scores might thus serve as a proxy for financial sophistication (e.g. Agarwal, Rosen, and Yao, 2016; Amromin, Huang, Sialm, and Zhong, 2018; Bhutta, Fuster, and Hizmo, 2021). Our results are consistent with this interpretation.

We first provide quasi-experimental evidence that reward credit cards induce low-FICO consumers to overborrow on their credit cards. 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 classic cards. We find that the spending response is stronger for consumers with a limit increase on re-

[2]See, for example, "Credit Cards Take From Poor, Give to the Rich" in the Wall Street Journal, and more recently "How credit card companies reward the rich and punish the rest of us" at Brookings, and "The ugly truth behind your fancy rewards credit card"at Vox.

ward cards and that this effect is present in all FICO groups. However, while prime and super-prime consumers also exhibit a proportional increase in credit card payments, this is not the case for sub-prime and near-prime consumers. As a result, following a limit increase on reward cards relative to classic cards, unpaid balances increase more for low-FICO consumers, while they remain unchanged for high-FICO consumers. This pattern is consistent with the documented tendency of naïve consumers to overborrow on their credit cards (Heidhues and Kőszegi, 2010; 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 strongly correlated with mistake-based measures of financial sophistication, as suggested by Calvet, Campbell, and Sodini (2009) and Jørring (2022), and that this association is more pronounced on reward cards. Focusing on individuals with multiple credit cards at the same bank, we follow Ponce, Seira, and Zamarripa (2017) and Gathergood, Mahoney, Stewart, and Weber (2019) and calculate the share of misallocated credit card payments.[3] 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 classic cards. We also show that low-FICO consumers in particular tend to follow a sub-optimal (and costly) balance-matching heuristic when repaying their credit cards. In line with the sub-optimal repayment behavior of naïve consumers (Kuchler and Pagel, 2021), these findings provide further corroborative evidence that the observed redistribution across FICO scores is driven by financial sophistication.

Next, we turn to the supply side and study reward credit cards from the banks' perspective, investigating both pricing strategies and profits. Despite reward cards incurring additional expenses for banks, we find that banks offer lower annual percentage

[3]Given the total repayment amount, the optimal, interest-minimizing repayment behavior 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 allocate further payments to subsequently cheaper cards. We calculate the share of misallocated payments as the difference between this optimal and the actually observed payment behavior as a mistake-based measure of financial sophistication.

rates (APRs) on reward cards than on similar classic cards across the entire FICO distribution, suggesting that banks incentivize the use of reward cards. How does this pricing strategy affect banks' profitability of reward and classic cards? We define a bank's profits on a credit card as the sum of income from interest payments, fee payments, and interchange fees, minus reward expenses, realized charge-offs, and funding costs for revolving balances. We find that banks profit from reward cards across all FICO scores, but that profits are highest for near-prime and prime cardholders in the middle of the FICO distribution. We further document substantial differences regarding banks' sources of revenue between high- and low-FICO consumers. For sub-prime cardholders, more than 60 percent of banks' revenues stem from interest income, while for super-prime cardholders, up to 80 percent stem from interchange income.

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 correlated with socio-demographic variables. We find that average net rewards are higher in ZIP codes with higher education levels, with a higher average income, and with a lower share of Black residents. Credit card rewards thus transfer income from less to more educated, from poorer to richer, and from high- to low-minority areas, thereby widening existing spatial disparities.

Our contribution to the literature is threefold. First, we empirically quantify the redistribution from naïve to sophisticated consumers, which has largely been studied theoretically. DellaVigna and Malmendier (2004) and Heidhues and Kőszegi (2010) model the contract design of profit-maximizing firms and show that firms can exploit the time-inconsistent preferences of naïve consumers by charging back-loaded fees. In Gabaix and Laibson (2006) and Heidhues and Kőszegi (2017), products with this type of pricing schemes benefit sophisticated consumers at the expense of naïve consumers and the latter cross-subsidize the former. Two recent papers empirically study such redistribution in the context of mortgage markets. For Italy, Guiso, Pozzi, Tsoy, Gambacorta, and Mistrulli (2021) report a subsidy from naïve to sophisticated households of 303 euros per year, induced by banks steering naïve households towards sub-optimal mortgages. For the United Kingdom, Fisher, Gavazza, Liu, Ramadorai, and Tripathy (2021) find that counterfactual mortgage rates without cross-subsidization would be 20 basis points higher than the teaser rates which benefit sophisticated households. Our paper, in contrast, studies redistribution in the credit card market induced by reward programs. Our empirical setting combined with our unique data enable us to readily quantify the costs (interest and fee payments) and, importantly, also the benefits (rewards) of financial product usage in monetary terms, thereby allowing for a straightforward estimation of the redistribution from naïve to sophisticated consumers.

Second, we contribute to the literature on reward credit cards, which has largely focused on interchange fees as a source of funding for credit card rewards. Interchange fees get passed through to merchants, which potentially respond by increasing retail prices for all consumers. Thus, 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. Hayashi (2009) provides a comprehensive overview of the market for credit card reward programs. Schuh, Shy, and Stavins (2010) study the redistribution from cash to credit card users and report an annual monetary transfer of $149 per cash-using household. Felt, Hayashi, Stavins, and Welte (2020) also study the redistribution from cash to credit card users and find that they imply a transfer from low-income to high-income consumers. The legal literature has also documented this regressive redistribution, relating it to a stronger need for consumer protection (e.g., Levitin, 2008; Sarin, 2019). In contrast, our study focuses on the redistribution within credit card users, which is, as we argue, a more important margin. We show that the relevant transfer is from naïve to sophisticated consumers rather than across income cohorts.

Third, 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, Michaud, and Mitchell, 2017; Bach, Calvet, and Sodini, 2020; Campbell, Ramadorai, and Ranish, 2019). In particular, our main finding that rewards 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, Georgarakos, and Inderst, 2019) and financial sophistication (Fagereng, Guiso, Malacrino, and Pistaferri, 2020).

II. Credit Card Rewards Programs

Credit card rewards—in the form of cash back, miles, or points—are loyalty programs by banks which offer various benefits to cardholders per dollar spent on the credit card. Cash back cards refund a small percentage amount of the net purchase volume (usually between 0.5 and 3 percent), while miles and points cards let cardholders accrue bonus points that can be redeemed at frequent flyer programs (miles cards) or, more generally, at partnering airlines, hotels, or retailers (points cards). Reward credit cards are a ubiquitous and increasingly important aspect of consumer 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. 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 an incentive scheme to induce consumers to adopt and increase the usage of the banks' credit card products (Agarwal, Chakravorti, and Lunn, 2010; Ching and Hayashi, 2010).

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.[4] Following Felt, Hayashi, Stavins, and Welte (2020), consider the example of a cardholder making a $100 purchase with a reward credit card.

[4] See also Hayashi (2009), Shy and Wang (2011), and Felt, Hayashi, Stavins, and Welte (2020) for further discussion of the underlying market structure of credit card payments and rewards.

This payment initially flows from the cardholder to the card-issuing bank, which in turn rewards the cardholder with, for instance, $1 in cash back, 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, Shy, and Stavins, 2010; Felt, Hayashi, Stavins, and Welte, 2020).

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, Greene, and Stavins, 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 is likely more important than the transfer from cash to card users in recent years.

Contrasting the $34.8 billion in rewards expenses with the combined $99.6 billion earned in interest and credit card fees 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.

III. Data and Summary Statistics

A. 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 data on cardholders' accumulated rewards, interest and fee payments, purchase volumes, FICO credit scores, credit limits, and further card characteristics. We also obtain data on the card issuing bank as well as the cardholders' ZIP code.

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 fees paid on card i in month t from the rewards earned on the card during the same period:[5]

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

[5]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 in detail the estimation of monthly rewards from the variables in our dataset. Our data, by construction, do not capture non-pecuniary rewards associated with reward credit cards (e.g., access to airport lounges). In that respect, what we measure is a lower bound of cardholders' net rewards.

Cardholders with positive net rewards thus benefit from the use of credit cards, while cardholders with negative net rewards pay for the use of credit cards.

Our analysis focuses on the cross section of all credit cards in March 2019.[6] We focus on general purpose and private label, unsecured, consumer credit cards with a revolving feature. We further exclude corporate credit cards and closed accounts. This sample construction procedure results in sample of about 238 million credit cards as of March 2019.

B. Summary Statistics

Table I 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 classic cards (n^C=117,842,925). Panel A presents variables related to the calculation of net rewards. The average reward card earns $9 in monthly rewards and the average classic card—by definition—zero. However, reward cards also exhibit on average higher interest charges than classic 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 classic card.

[Table I about here]

Panel B presents other card-level variables. On average, reward cards have lower APRs than classic cards (18% versus 22%), yield higher bank profits per card in a given month ($23 versus $6), and have higher credit limits ($10 thousand versus $4 thousand).[7] 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 classic cards, respectively.

[6]We focus on March 2019 as a recent month before the COVID-19 pandemic which is also not subject to seasonal effects in consumption (such as December).

[7]We describe the calculation of card-level bank profits in detail in Section VII.B.

Cardholders of reward cards have, on average, higher FICO scores than cardholders of classic 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.

IV. Redistribution in the Credit Card Market

A. Empirical Approach

To study the extent to which credit card rewards generate a redistribution between consumers and what drives this redistribution, we compare credit card outcomes between reward cards and classic 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 individual j. Our baseline regression specification is then given by:

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

where *Reward Card* is a dummy variable which takes the value 1 for reward cards and 0 for classic 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. To avoid endogeneity problems 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. $\alpha_{b,z,w,f}$ are interacted fixed effects at the Bank $\times$ ZIP code $\times$ Income percentile $\times$ FICO percentile level. That is, we compare credit card outcomes between reward and classic 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*. We control for the following card-level characteristics X: the credit limit (in dollar terms), the amount past due (in dollar terms), the age of the card (in years), 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.

B. *Net Rewards*

Figure 1 illustrates the magnitude of net rewards across the FICO distribution and point to a clear redistribution between cardholders. For both reward cards and classic cards, average net rewards are increasing in FICO scores, suggesting that low-FICO consumers pay more for credit card usage. The relative magnitudes between the two card types, however, differ substantially across FICO scores. For cardholders with super-prime scores (above 780), net rewards are on average positive for reward cards and slightly negative for classic cards.[8] 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

[8]Note that the net rewards of classic cards can—by definition—at best be zero if consumers incur no interest or fee payments.

cards and -$25 for classic cards. On average, low-FICO cardholders lose money with reward cards, both in absolute dollar terms and relative to classic cards.

[Figure 1 about here]

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 II present the estimation 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 include, alternatively, Bank $\times$ ZIP code $\times$ Income percentile (column 1), Bank $\times$ ZIP code $\times$ FICO score percentile (column 2), and Bank $\times$ ZIP code $\times$ Income percentile $\times$ FICO score percentile (column 3) fixed effects. All specifications show that net rewards are significantly higher for reward cards than for similar classic cards. The coefficient of our preferred and most stringent specification in column (3) indicates that a reward card, on average, yields a $3.5 higher net reward than a very similar classic card.

[Table II about here]

This average net reward differential between reward and classic cards, however, masks important differences between cardholders across the FICO distribution. Taking the specification in column (3) as our baseline, column (4) reports the differences in net rewards between reward and classic cards, separately for sub-prime, near-prime, prime, and super-prime cardholders. Consistent with Figure 1, net rewards for sub-prime and near-prime cardholders are between $5.4 and $6.8 lower on reward cards than on similar classic cards. On the other end of the FICO distribution, net rewards turn positive and are, on average, $7.3 and $16.0 higher for prime and super-prime cardholders, respectively. Thus, while reward cards are more beneficial than classic cards on average, only high-FICO consumers gain from them, while low-FICO consumers would be better off choosing classic cards, other things equal.[9]

Robustness. 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 I, reward cards tend to have lower APRs and higher credit limits than classic cards. Individuals might therefore chose to hold 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 III 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. 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.

[Table III about here]

Our dataset further contains a unique individual identifier within banks which allows us to compare credit card outcomes between reward and classic cards within the same cardholder j. Restricting our sample to the set of individuals who own at least one reward card and one classic card at the same bank, we can estimate our baseline specification with cardholder fixed effects, thus comparing the outcomes of reward and classic cards *within the same individual*. As shown in columns (5) and (6) of Table III, we obtain quantitatively similar results as in our baseline specification in Table II. One limitation of our dataset is the impossibility to track individuals across banks. Thus, the interpretation of these results is subject to the caveat that individuals might hold additional,

[9]To show that our regression results are not driven by our threshold values for the different FICO buckets, Figure A1 in Online Appendix C 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.

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 classic) 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. Cardholders with negative net rewards in aggregate pay \$4.1 billion for the use of reward cards and cardholders with positive net rewards earn \$1.3 billion.[10] The monthly \$1.3 billion positive net rewards translate into an annualized redistribution of \$15.1 billion induced by reward credit cards. Of the \$4.1 billion that are paid by cardholders with negative net rewards, \$1.0 billion come from sub-prime, \$1.6 billion from near-prime, \$1.1 billion from prime, and only \$0.4 billion from super-prime cardholders. Of the \$1.3 billion earned by cardholders with positive net rewards, only \$35 million go to sub-prime, \$134 million to near-prime, \$407 million to prime, and \$680 million 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.

C. 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 2 illus-

[10]Table A1 in Online Appendix D summarizes our aggregate findings. The difference of \$2.9 billion constitutes bank income. We study the banks' perspective on reward credit card in Section VII.

trates 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.[11] While interest charges are generally higher for reward cards than for classic cards, this difference is largest for near-prime cardholders in the left part of the distribution.

[Figure 2 about here]

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 IV. Rewards are on average \$6.4 higher on reward cards than on classic 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 classic cards, while for super-prime cardholders interest charges are \$7.1 lower (column 4). Finally, fee charges are economically less relevant: the difference between reward and classic 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.

[Table IV about here]

[11] Figure A3 in Online Appendix C additional illustrates total fee charges, which are substantially smaller in magnitude relative to interest charges.

V. 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 cash back" (Stewart, 2021).[12]

Our results, however, show that this explanation is at best incomplete. First, FICO scores and income are only moderately correlated, as documented in Beer, Ionescu, and Li (2018). This allows us to study net rewards across the FICO distribution within different income groups.[13] 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.

Figure 3 illustrates the magnitude of net rewards for reward cards across the FICO distribution for the three income groups.[14] 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-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

[12]See also "Credit Cards Take From Poor, Give to the Rich" (Derby, 2010) in the Wall Street Journal.

[13]Figure A4 shows that, while the distributions of FICO scores shifts to the right when moving from low- to high-income cardholders, they strongly overlap, suggesting that within given FICO buckets there are individuals with very different income levels.

[14]For ease of exposition, Figure 3 only plots net rewards for reward cards. Panel A of Figure A5 in Online Appendix C additionally plots net rewards for classic cards. Additionally, Panel B of Figure A5 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 A6 further illustrates the magnitude of net rewards across income percentiles, showing that there is no clear pattern in net rewards across the income distribution.

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.

[Figure 3 about here]

Table V 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 classic cards in all income groups. While average net rewards are increasing with income, 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.

[Table V about here]

The combined results in Figure 3 and Table V show that, on average, high-income consumers with high FICO scores benefit from reward credit cards largely at the expense of high-income consumers with low FICO scores.[15] Hence, our findings are not primar-

[15]Table A4 in Online Appendix D further substantiates this finding by showing very similar results for the top 10% and 5% of the income distribution, respectively.

ily driven by income and therefore inconsistent with a "reverse Robin Hood" mechanism.

VI. 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, Campbell, and Sodini, 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 sub-optimal 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.[16] Consequently, individuals with higher (lower) FICO scores have been found to incur lower (higher) interest payments, fee payments, and charge-offs (Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2015). FICO scores thus capture the same type of credit card behavior that is associated with a lack of financial sophistication, namely overindebtedness and sub-optimal repayment behavior. Therefore, a large stream of the existing literature uses FICO scores as a measure for financial sophistication (Agarwal, Rosen, and Yao, 2016; Amromin, Huang, Sialm, and Zhong, 2018; Bhutta, Fuster, and Hizmo, 2021).

A. Overindebtedness

We first study whether reward cards induce consumers to incur higher levels of unpaid balances relative to classic cards and whether, consistent with the interpretation of FICO scores as a proxy measure for financial sophistication, this effect is stronger

[16] https://www.myfico.com/credit-education/whats-in-your-credit-score

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.[17] The ideal experiment would randomly assign a reward feature to a classic card and then track changes in credit card outcomes over time. We approximate this experiment by studying the differential spending and borrowing responses of reward and classic cards to increases in credit card limits and therefore an increase in credit supply (Gross and Souleles, 2002; Aydin, 2022).

We collect all credit cards which received a *bank-initiated* credit limit increase in March 2019, the month of our cross-sectional analysis.[18] 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 classic cards in a standard difference-in-differences setting:

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

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.[19] As in Equation (2), *Reward Card* takes the value 1 for reward cards and 0 for classic cards, and D^F is a set of FICO bucket dummy variables 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 $\times$ ZIP code fixed effects, the standard set of card- and cardholder-

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

[18]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.

[19]Table A6 in Online Appendix D provides a robustness check which only considers the cards with a credit limit increase, finding qualitatively similar results.

level control variables, and further income, FICO scores, spending, and payments, all measured by their pre-treatment averages.[20]

Table VI 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 classic cards (column 1). The difference is economically meaningful and amounts to $76, which corresponds to about 9% of average monthly spending. We also find a differential increase in repayments, albeit smaller in magnitude ($32, column 3). As a result, unpaid balances on reward cards increase compared to similar classic cards ($19), suggesting that an increase in credit limits on reward cards induces consumers to overborrow relative to classic cards.

[Table VI about here]

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 (column 4). In contrast, for low-FICO consumers the increase in payments is statistically insignificant and close to zero in magnitudes. As a result, credit limit increases on reward cards yield a significant increase in unpaid balances for sub-prime ($33.8) and near-prime ($25.3) consumers, while unpaid balances do not change significantly for high-FICO consumers (column 6). These results suggest that credit card rewards induce sub- and near-prime consumers to overspend and subsequently overborrow on their credit cards, consistent with the interpretation of FICO scores as a measure for financial sophistication (Grubb, 2015; Lusardi and Tufano, 2015).

[20]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.

B. *Sub-Optimal 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 financial products (Calvet, Campbell, and Sodini, 2009; Jørring, 2022). Specifically, we follow Ponce, Seira, and Zamarripa (2017) and Gathergood, Mahoney, Stewart, and Weber (2019) and calculate the share of misallocated repayments for consumers with multiple credit cards at the same bank.[21] 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.

We first plot the share of misallocated payments at the borrower level across the FICO distribution, aggregated over both reward cards and classic cards. Panel A of Figure 4 shows that misallocated payments are decreasing in FICO scores, consistent with high-FICO consumers being more financially sophisticated. Panel B of Figure 4 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 classic cards. Sub-prime cardholders, in contrast, misallocate up to 14 percent of all credit card repayments on reward cards and around 8 percent on classic cards.

[Figure 4 about here]

We next estimate Equation (2) with the share of misallocated payments as the outcome variable. Table VII 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

[21] 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. We describe the calculation of the misallocated payment share in detail in Online Appendix B.

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 classic cards (column 5). This result is exclusively 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 classic cards for prime- and super-prime cardholders. Thus, reward cards do not only induce low-FICO consumers to overborrow, but also to engage in sub-optimal repayment behavior. These results also hold true when relaxing some of the sample restrictions (columns 1-4).[22]

[Table VII about here]

Finally, we follow Gathergood, Mahoney, Stewart, and Weber (2019) and show that cardholders follow a sub-optimal 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 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 VIII, actual payments are most strongly correlated with the balance-matching heuristic, in line with Gathergood, Mahoney, Stewart, and Weber (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, sub-optimal repayment behavior tends to be more severe for low-FICO consumers.

[Table VIII about here]

[22]Results are also robust to restricting the sample to individuals with only two cards—see Table A7 in Online Appendix D.

Overall, our findings in Section VI are consistent with the hypothesis that reward cards exploit the over-borrowing and sub-optimal 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, Campbell, and Sodini, 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, Mullainathan, and Shafir, 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.

VII. The Banks' Perspective: Pricing and Profits

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

A. Pricing

We first study the interest rates offered by banks on reward cards relative to comparable classic cards. Panel A of Figure 5 shows that the average annual percentage rate

(APR) of interest on reward cards is systematically lower than interest rates on classic cards across the entire FICO distribution.[23]

[Figure 5 about here]

This pattern is confirmed in our standard regression setting, estimating Equation (2) with APRs as the outcome variable. Columns (1) and (2) of Table IX present the results. Across all cardholders, APRs on reward cards are on average 1.0 percentage points lower than on comparable classic cards. This interest rate differential between reward and classic 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.

[Table IX about here]

B. *Bank Profits*

At *prima facie*, offering lower interest rates on reward cards than on comparable classic cards to increase the number of reward cards may not appear as a profit-maximizing strategy. However, the evidence on higher interest and fee charges for reward cards (Figure 2) suggests that, even if with lower prices, 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:

$$\text{Profit}_i = \text{Interest Paid}_i + \text{Total Fees}_i + \text{Interchange Income}_i \tag{4}$$

$$- \text{Rewards}_i - \text{Realized Charge-Offs}_i - \text{WACC} \times \text{Unpaid Balances}_i \tag{5}$$

[23]Given that all credit card accounts in the sample are initiated at least 12 months prior to March 2019, the lower APR on reward cards relative to classic cards does not reflect zero or low APRs during potential promotional periods.

The variables *Interest Paid*, *Total Fees*, and *Rewards* are defined as in Section III. Whereas interest and fees represent payments from the cardholder's perspective, they represent income from the bank's perspective. Conversely, whereas rewards represent income from the cardholder's perspective, they represent costs from the bank's perspective. Our analysis of bank profitability also introduces three new terms which are not included in the previous analysis: *Interchange Income*, *Realized Charge-Offs*, and *WACC*$\times$ *Unpaid Balances*. As discussed in Section II, 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). We assess interchange income at the card level to be 1.5 percent of the purchase volume for classic cards and 2.5 percent for reward cards. Realized charge-offs are an expense incurred by the bank on accounts that remain delinquent for 180 days and for which the outstanding balance can no longer be considered an asset on the balance sheet (CFPB, 2019). From the cardholder's perspective, charge-offs do not matter for the net cash flow on a credit card. From a bank's perspective, however, realized charge-offs are an important determinant of the ex-post profitability of an account and we therefore include them in the definition of banks' profits. The third term captures banks' cost of financing revolving credit card balances. We assess these costs at a conservative 5 percent weighted average cost of capital (WACC).

Panel B of Figure 5 shows that bank profits are hump-shaped in FICO scores and substantially higher on reward than on classic cards across the entire FICO distribution. Columns (3) and (4) of Table IX present the estimation results of Equation (2) with bank profits as the outcome variable. Across all cardholders, bank profits are about \$7.4 higher on reward cards than on comparable classic 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 (\$15.3) and prime (\$9.0) cardholders in the middle of the FICO distribution. For sub-prime cardholders, which tend to incur the highest charge-offs, profits are also higher on rewards cards, but with the differential being smaller in magnitude ($4.1). For super-prime cardholders, which tend to earn a lot of rewards and also incur low interest payments, bank profits are only $1.3 higher on reward than on classic cards. Thus, from the banks' perspective, near-prime and prime cardholders are the largest source of profits in the market for reward credit cards.

There are also substantial differences in banks' sources of revenue across the FICO distribution. Figure 6 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 across the FICO distribution.

[Figure 6 about here]

VIII. 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 7 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.

[Figure 7 about here]

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 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 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.

As shown in columns 1,3, and 5 of Table X, higher net rewards are associated with a higher level of educational attainment, with a higher median income, and with a lower share of Black residents. These results suggest that credit card rewards are a potential channel that can exacerbate existing socio-economic disparities across regions in the United States, as they imply a transfer from less to more educated, from poorer to richer, and from high- to low-minority areas, thereby widening existing spatial disparities.[24] Columns 2,4, and 6 illustrate that all coefficients become statistically insignificant and close to zero in magnitude when controlling for a ZIP code's average FICO score, indicating that differences in financial sophistication are the underlying mechanism driving our geographical results.

[24]Although FICO scores and income are only moderately correlated, as discussed in Section V, high FICO scores are still more prevalent among high-income cardholders, as shown in Figure A4. Thus, while our card-level results are not driven by differences in income, we still find a positive correlation between net rewards and income in our aggregate ZIP code-level analysis.

[Table X about here]

IX. 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 classic 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.

REFERENCES

Agarwal, Sumit, Sujit Chakravorti, and Anna Lunn, 2010, Why do banks reward their customers to use their credit cards?, Federal Reserve Bank of Chicago Working Paper 2010-19.

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel, 2015, Regulating consumer financial products: Evidence from credit cards, Quarterly Journal of Economics 130, 111–164.

Agarwal, Sumit, Richard J. Rosen, and Vincent Yao, 2016, Why do borrowers make mortgage refinancing mistakes?, Management Science 62, 3494–3509.

Amromin, Gene, Jennifer Huang, Clemens Sialm, and Edward Zhong, 2018, Complex mortgages, Review of Finance 22, 1975–2007.

Aydin, Deniz, 2022, Consumption Response to Credit Expansions: Evidence from Experimental Assignment of 45,307 Credit Lines, American Economic Review 112, 1–40.

Bach, Laurent, Laurent E. Calvet, and Paolo Sodini, 2020, Rich Pickings? Risk, Return, and Skill in Household Wealth, American Economic Review 110, 2703–2747.

Beer, Rachael, Felicia Ionescu, and Geng Li, 2018, Are income and credit scores highly correlated?, FEDS Notes August 13, 2018.

Bhutta, Neil, Andreas Fuster, and Aurel Hizmo, 2021, Paying too much? Borrower sophistication and overpayment in the us mortgage market, CEPR Discussion Paper DP14924.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2009, Measuring the financial sophistication of households, American Economic Review 99, 393–398.

Campbell, John Y., 2006, Household finance, Journal of Finance 61, 1553–1604.

Campbell, John Y., 2016, Restoring rational choice: The challenge of consumer financial regulation, American Economic Review: Papers & Proceedings 106, 1–30.

Campbell, John Y., and Joao F. Cocco, 2003, Household risk management and optimal mortgage choice, Quarterly Journal of Economics 118, 1449–1494.

Campbell, John Y., Tarun Ramadorai, and Benjamin Ranish, 2019, Do the Rich Get Richer in the Stock Market? Evidence from India, American Economic Review: Insights 1, 225–240.

CFPB, 2019, The consumer credit card market, Report .

Ching, Andrew T., and Fumiko Hayashi, 2010, Payment card rewards programs and consumer payment choice, Journal of Banking & Finance 34, 1773–1787.

DellaVigna, Stefano, and Ulrike Malmendier, 2004, Contract design and self-control: Theory and evidence, Quarterly Journal of Economics 119, 353–402.

Derby, Michael S., 2010, Credit cards take from poor, give to the rich, Wall Street Journal July 27, 2010, https://www.wsj.com/articles/BL-REB-11033.

Deuflhard, Florian, Dimitris Georgarakos, and Roman Inderst, 2019, Financial Literacy and Savings Account Returns, Journal of the European Economic Association 17, 131–164.

Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri, 2020, Heterogeneity and Persistence in Returns to Wealth, Econometrica 88, 115–170.

Felt, Marie-Hélène, Fumiko Hayashi, Joanna Stavins, and Angelika Welte, 2020, Distributional Effects of Payment Card Pricing and Merchant Cost Pass-through in the United States and Canada, Federal Reserve Bank of Kansas City, Research Working Paper 20-18.

Fisher, Jack, Alessandro Gavazza, Lu Liu, Tarun Ramadorai, and Jagdish Tripathy, 2021, Refinancing cross-subsidies in the mortgage market, Bank of England Staff Working Paper 948.

Foster, Kevin, Claire Greene, and Joanna Stavins, 2021, The 2020 survey of consumer payment choice: Summary results, Federal Reserve Bank of Atlanta Research Data Report .

Gabaix, Xavier, and David Laibson, 2006, Shrouded attributes, consumer myopia, and information suppression in competitive markets, Quarterly Journal of Economics 121, 505–540.

GAO, 2009, Government accountability office: Rising interchange fees have increased costs for merchants, but options for reducing fees pose challenges, Report to Congressional Addressees .

Gathergood, John, 2012, Self-control, financial literacy and consumer over-indebtedness, Journal of Economic Psychology 33, 590–602.

Gathergood, John, Neale Mahoney, Neil Stewart, and Jörg Weber, 2019, How do individuals repay their debt? The balance-matching heuristic, American Economic Review 109, 844–875.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, 2021, Household finance, Journal of Economic Literature 59, 919–1000.

Gross, David B., and Nicholas S. Souleles, 2002, Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data, Quarterly Journal of Economics Volume 117, 149–185.

Grubb, Michael D., 2015, Overconfident Consumers in the Marketplace, Journal of Economic Perspectives 29, 9–36.

Guiso, Luigi, Andrea Pozzi, Anton Tsoy, Leonardo Gambacorta, and Paolo Emilio Mistrulli, 2021, The cost of steering in financial markets: Evidence from the mortgage market, Journal of Financial Economics 143, 1209–1226.

Hayashi, Fumiko, 2009, Do U.S. consumers really benefit from payment card rewards?, Economic Review 94, 37–63.

Heidhues, Paul, and Botond Kőszegi, 2010, Exploiting naïvete about self-control in the credit market, American Economic Review 100, 2279–2303.

Heidhues, Paul, and Botond Kőszegi, 2017, Naïveté-based discrimination, Quarterly Journal of Economics 132, 1019–1054.

Jørring, Adam, 2022, Financial sophistication and consumer spending, Journal of Finance forthcoming.

Kuchler, Theresa, and Michaela Pagel, 2021, Sticking to your plan: The role of present bias for credit card paydown, Journal of Financial Economics 139, 359–388.

Levitin, Adam J., 2008, The Social Costs of Credit Card Merchant Restraints, Harvard Journal on Legislation 45, 1–58.

Lusardi, Annamaria, Pierre-Carl Michaud, and Olivia S. Mitchell, 2017, Optimal financial knowledge and wealth inequality, Journal of Political Economy 125, 431–477.

Lusardi, Annamaria, and Olivia S. Mitchell, 2014, The economic importance of financial literacy: Theory and evidence, Journal of Economic Literature 52, 5–44.

Lusardi, Annamaria, and Peter Tufano, 2015, Debt literacy, financial experiences, and overindebtedness, Journal of Pension Economics and Finance 14, 332–368.

Meier, Stephan, and Charles Sprenger, 2010, Present-biased preferences and credit card borrowing, American Economic Journal: Applied Economics 2, 193–210.

Ponce, Alejandro, Enrique Seira, and Guillermo Zamarripa, 2017, Borrowing on the wrong credit card? Evidence from Mexico, American Economic Review 107, 1335–1361.

Sarin, Natasha, 2019, Making consumer finance work, Columbia Law Review 119, 1519–1596.

Schuh, Scott, Oz Shy, and Joanna Stavins, 2010, Who gains and who loses from credit card payments? Theory and calibrations, Federal Reserve Bank of Boston Public Policy Discussion Papers 10-03.

Shah, Anuj K., Sendhil Mullainathan, and Eldar Shafir, 2021, Some Consequences of Having Too Little, Science 338, 682–685.

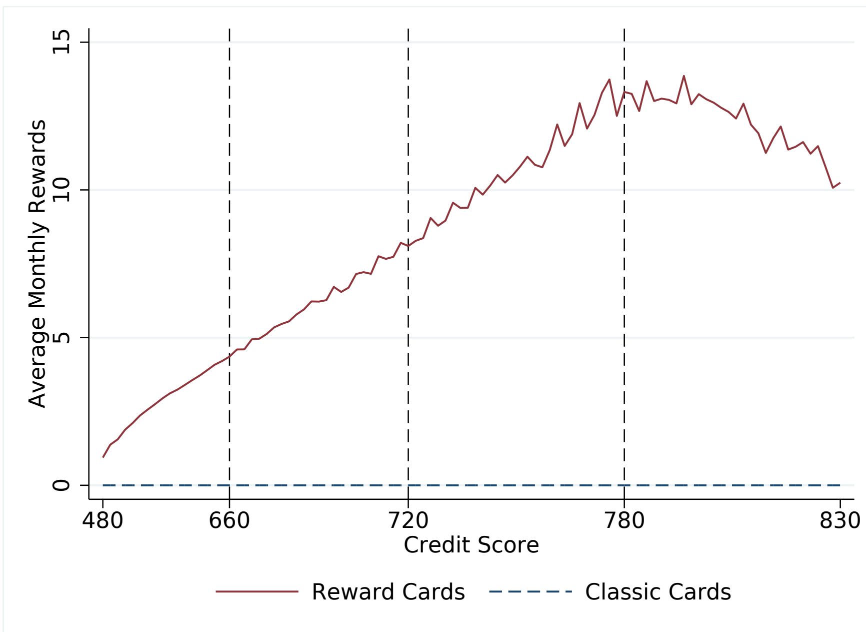
Shy, Oz, and Zhu Wang, 2011, Why do payment card networks charge proportional fees?, American Economic Review 101, 1575–1590.

Stewart, Emily, 2021, The ugly truth behind your fancy rewards credit card, vox.com June 3, 2021, https://www.vox.com/the-goods/22454885/who-pays-for-credit-card-rewards.

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 classic 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.

Figure 2. 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 classic 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

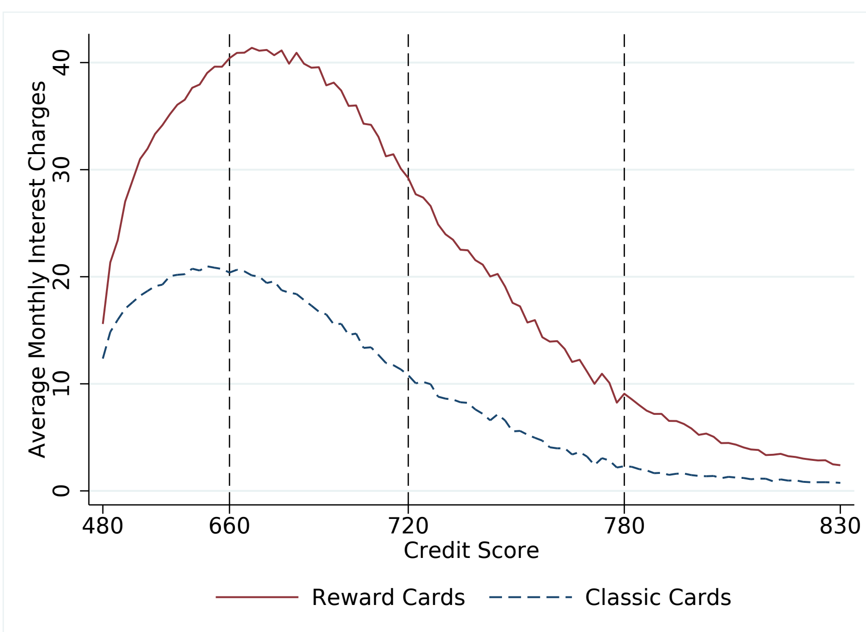


Figure 3. Net Rewards Across FICO Score Percentiles by Income Groups. This figure illustrates the dollar magnitude of average net rewards on reward cards across the FICO distribution by income groups. The red line plots the average net reward for borrowers with an annual income below 44 thousand, the 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 net reward (in dollar) 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.

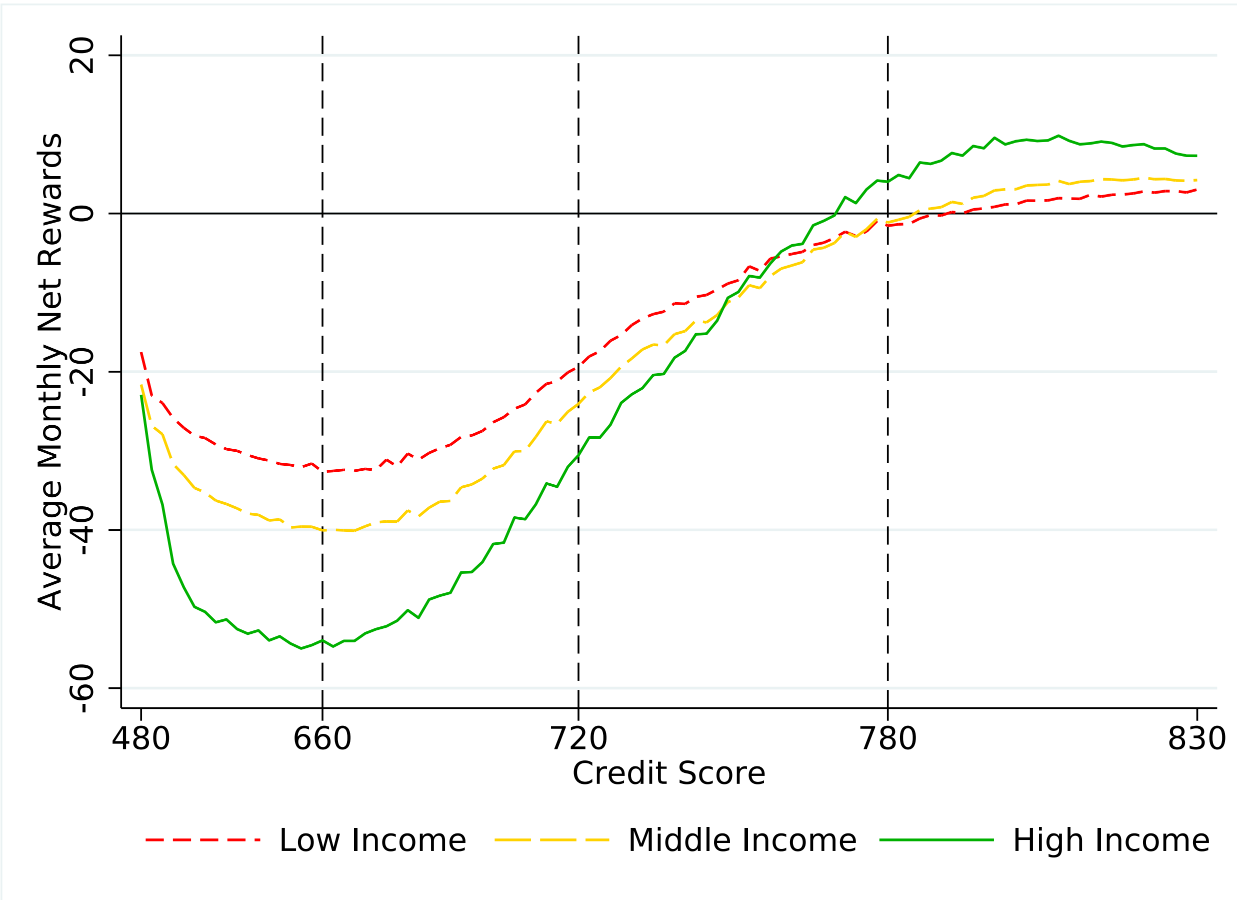
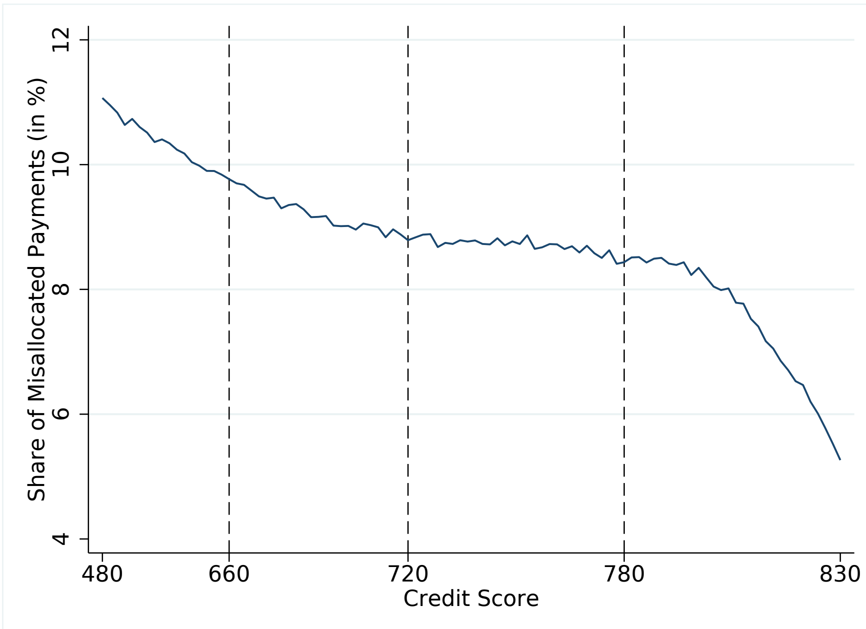


Figure 4. Share of Misallocated Payments Across FICO Score Percentiles. This figure illustrates the average percentage share of misallocated payments across the FICO distribution at the borrower level (Panel A) and separately for reward cards (solid red line) and classic cards (dashed blue line) (Panel 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.

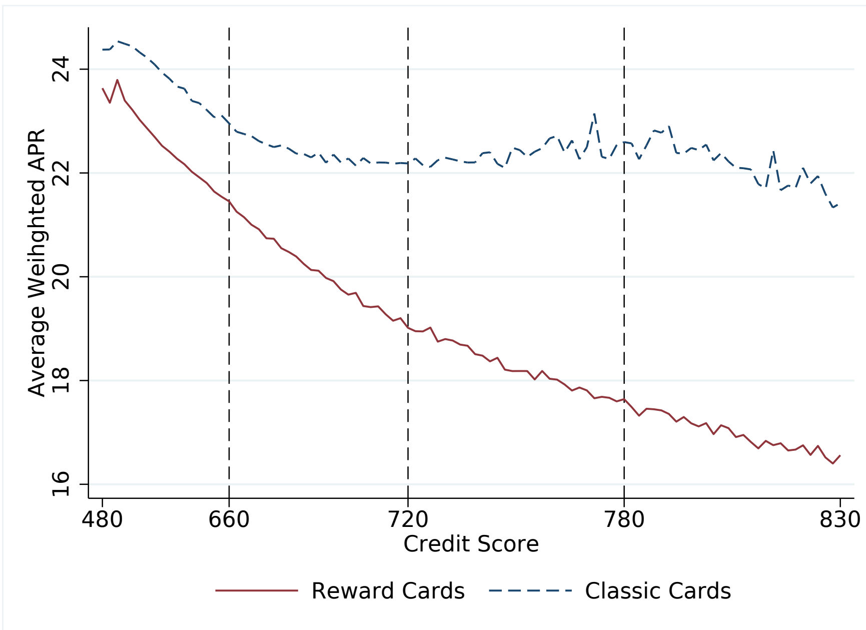
(A) Borrower Level



(B) Reward Cards versus Classic Cards

Figure 5. 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 classic 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

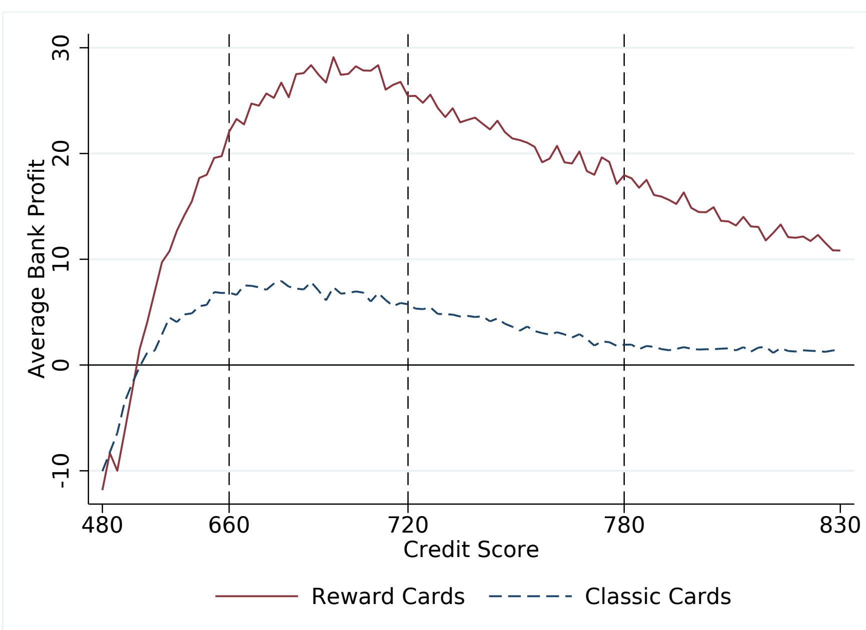
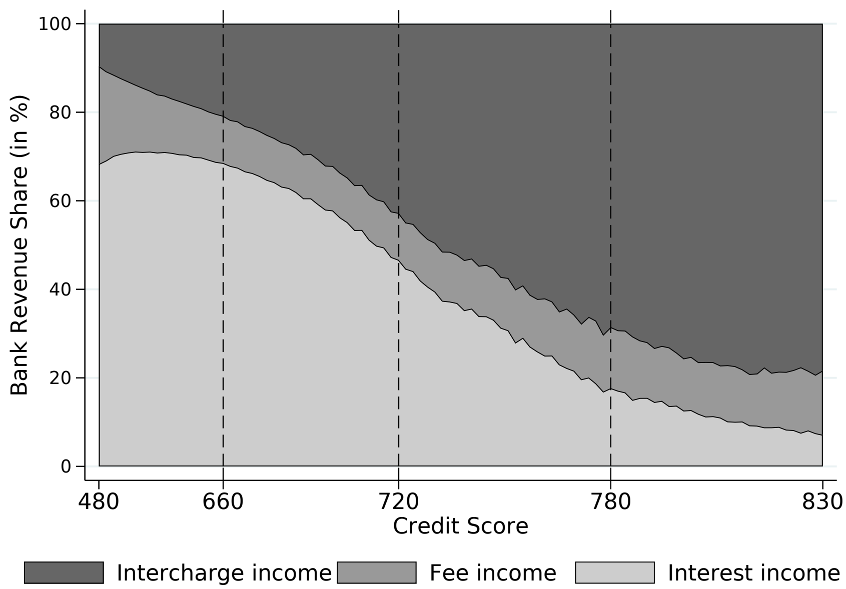


Figure 6. Bank Revenue Shares Across FICO Score Percentiles. This figure illustrates the average bank revenue share across the FICO distribution for 100 equal-sized FICO buckets between 300 and 850, separately for reward cards (Panel A) and classic cards (Panel B). For each card type, we plot the share 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) Classic cards

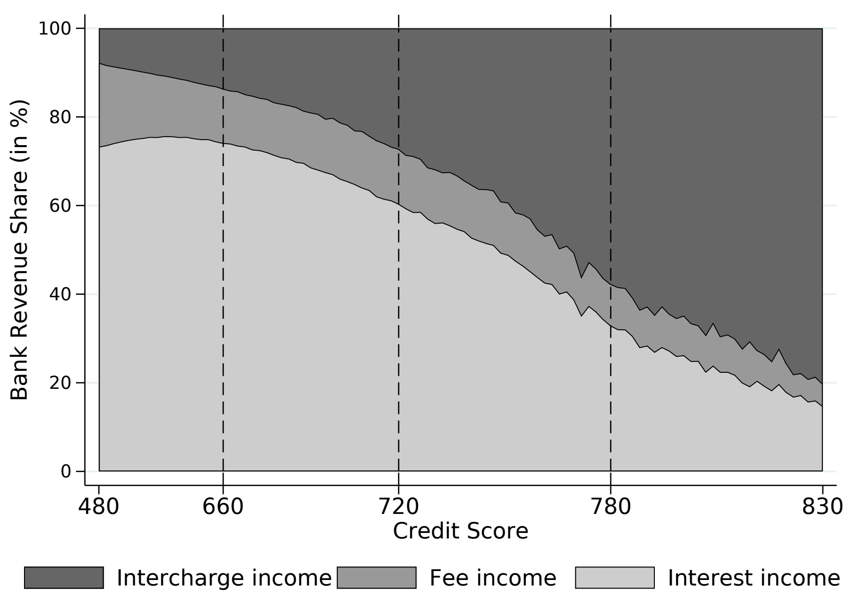
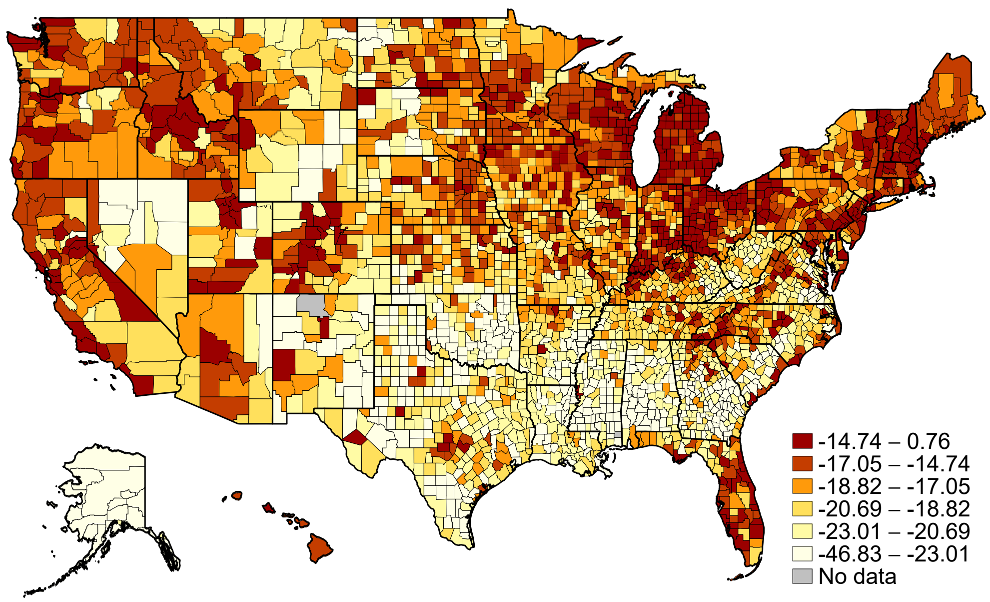


Figure 7. The Geography of Net Rewards and FICO Scores. This figure illustrates the average dollar amount of net rewards (Panel A) and the average FICO score (Panel B) across counties in the United States. The graph is based on our baseline sample of 238 million credit cards in March 2019.

(A) Average Net Rewards Across Counties



(B) Average FICO Scores Across Counties

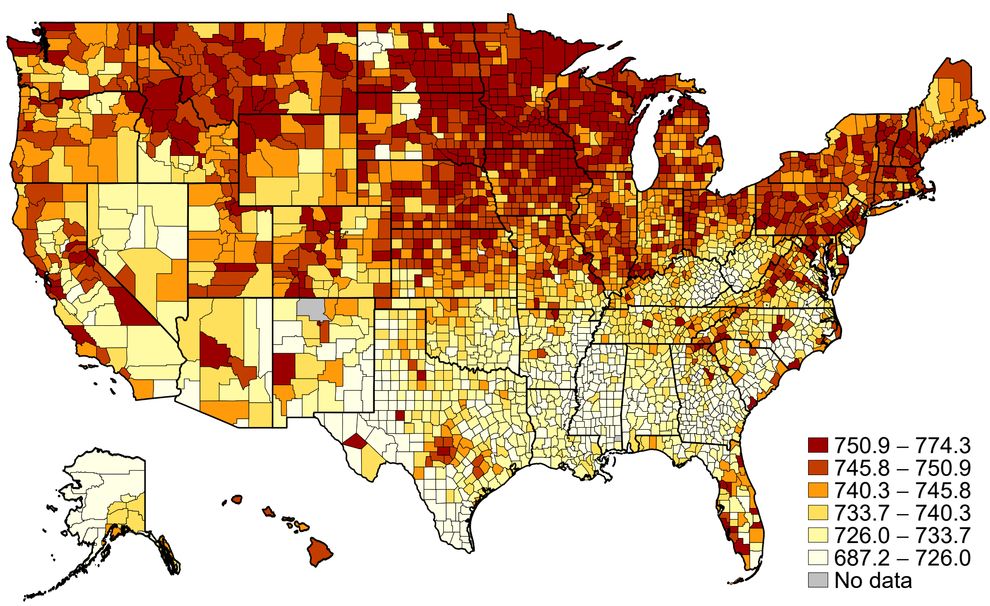


Table I. Summary Statistics

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 classic cards (Columns 4 and 5). Panel A presents variables related to the calculation of net rewards (as described in Section A). Panel B presents other card-level outcome and control variables used in our analysis.

	All Cards			Reward Cards	Classic Cards
	(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 (0/1)	0.02	0.00	0.15	0.03	0.02
Fraud Flag (0/1)	0.00	0.00	0.06	0.00	0.00
Deposit Relationship With Same Bank (0/1)	0.19	0.00	0.39	0.28	0.10
Lending Relationship With Same Bank (0/1)	0.08	0.00	0.27	0.11	0.05
No. Cards With Same Bank (0/1)	2.11	2.00	1.25	1.89	2.34
Workout Program (0/1)	0.01	0.00	0.07	0.00	0.01
Bankruptcy Flag (0/1)	0.00	0.00	0.05	0.00	0.00
Observations		237,573,278		119,730,353	117,842,925

Table II. Net Rewards: Baseline Results

This table presents the estimation results for differences in net rewards between reward cards and classic 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 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***
				(0.67)
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			

Table III. Net Rewards: Robustness Tests

This table presents robustness checks for the estimation results for differences in net rewards between reward cards and classic cards. The outcome variable is the net reward of card i as defined in Equation (1) in Section III. 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 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 3 and 4 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: Bank × Cardholder	-	-	-	-	Y	Y
FE: Bank × Zip × Income × FICO	-	-	Y	Y	-	-
FE: Bank × Zip × Income × FICO × Limit × APR	Y	Y	-	-	-	-
Observations	12,381,801				65,513,743	

Table IV. Net Reward Components

This table presents the estimation results for differences in net reward components between reward cards and classic cards from Equation (2) in Section IV.A. The outcome variables are the dollar amount of rewards (columns 1 an 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. 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: Bank × Zip × Income × FICO	Y	Y	Y	Y	Y	Y
Observations	237,573,278					

Table V. Net Rewards by Income Groups

This table presents the estimation results for differences in net rewards between reward cards and classic cards from Equation (2) in Section IV.A, 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 III. 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 Tercile of Income Distribution		Middle Tercile of Income Distribution		Upper Tercile of Income Distribution	
	(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: Bank × Zip × Income × FICO	Y	Y	Y	Y	Y	Y
Observations	75,159,536		79,540,729		82,873,013	

Table VI. Overindebtedness: Difference-in-Differences Analysis

This table presents the estimation results for the difference-in-differences regression in Equation (3) in Section VI.A. 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 classic 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 has. 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. 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	75.77***		31.96***		19.17**	
	(6.83)		(3.72)		(8.79)	
Reward Card × Sub-Prime		59.75***		5.06		33.82***
		(6.43)		(3.12)		(11.24)
Reward Card × Near-Prime		62.88***		4.53		25.25*
		(7.18)		(4.29)		(13.53)
Reward Card × Prime		89.03***		73.19***		4.83
		(7.98)		(6.17)		(12.16)
Reward Card × Super-Prime		164.85***		153.22***		-28.20
		(14.14)		(13.22)		(25.26)
Card Controls (Pre-Period)	Y	Y	Y	Y	Y	Y
Cardholder Controls (Pre-Period)	Y	Y	Y	Y	Y	Y
Income and FICO (Pre-Period)	Y	Y	Y	Y	Y	Y
Spending and Payments (Pre-Period)	Y	Y	Y	Y	Y	Y
FE: Bank × Zip	Y	Y	Y	Y	Y	Y
Observations	1,236,604					

Table VII. Share of Misallocated Payments

This table presents the estimation results for differences in the share of misallocated payments (as defined in Equation A5 in Section B) between reward cards and classic cards from Equation (2) in Section IV.A. 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	1.24***		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:						
At least two cards with revolving debt at the same bank	Y	Y	Y	Y	Y	Y
Not fully paid balance on all cards with revolving debt	Y	Y	Y	Y	Y	Y
Minimum payment on all cards with revolving debt and more than the minimum on at least one	N	N	Y	Y	Y	Y
Different APRs on all cards with revolving debt	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	

Table VIII. 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 VI.B: (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 classic cards (1 and 2).

	Payment on Reward Card(s)		Payment on Classic 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

Table IX. Annual Percentage Rates (APR) of Interest and Bank Profits

This table presents the estimation results for differences in net reward components between reward cards and classic cards from Equation (2) in Section IV.A. The outcome variables are the annual percentage rate of interest (APR) (columns 1 an 2) and the dollar amount of bank profits per card as defined in Equation 5 in Section VII.B (column 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. 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			

Table X. The Geography of Net Rewards

This table presents the estimation results for net rewards at the ZIP code-level from Equation (6) in Section VIII. 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					

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.[25] 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).

[25]This procedure yields 380 individual credit card product clusters. Table A2 in the appendix 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, Seira, and Zamarripa (2017) and Gathergood, Mahoney, Stewart, and Weber (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 4 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 classic 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.

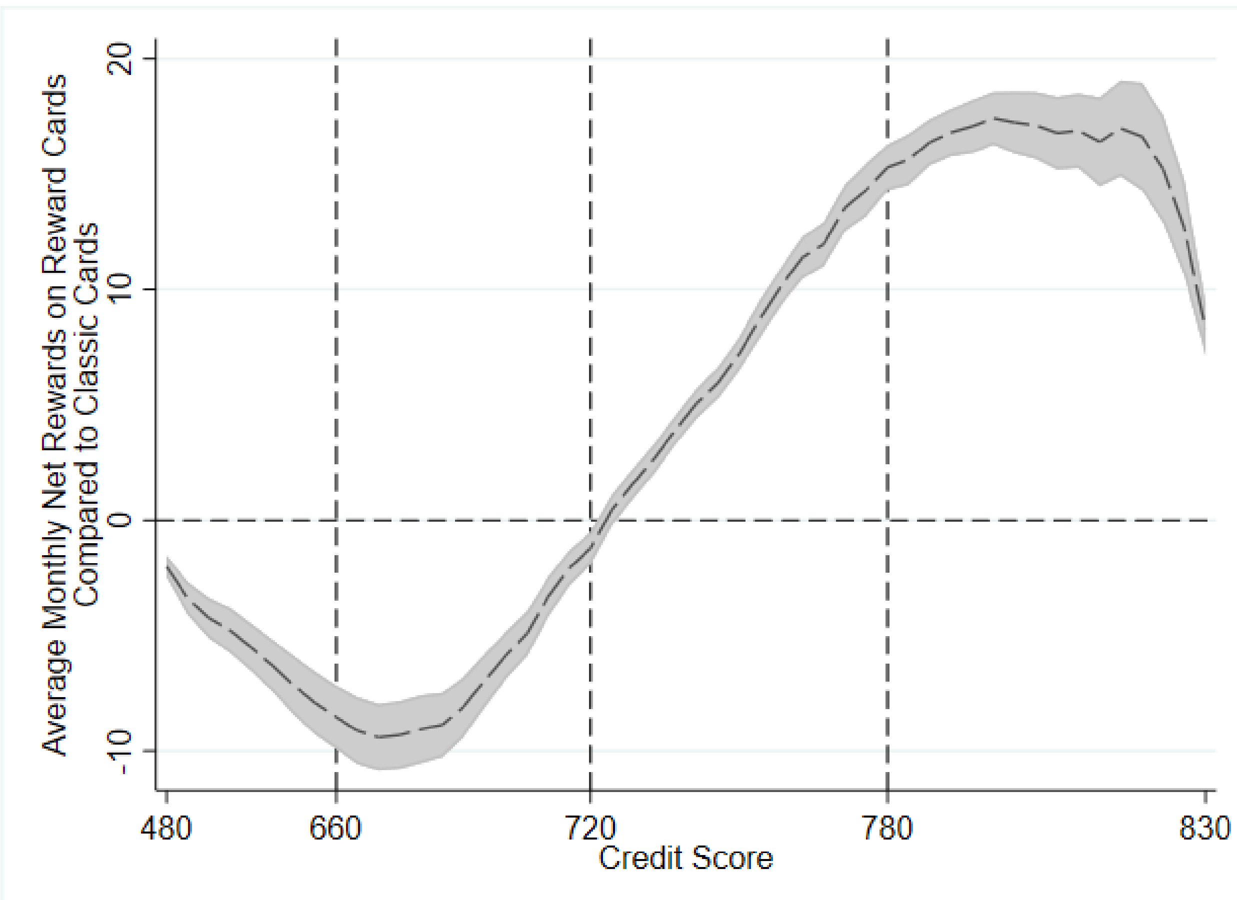


Figure A2. Net Rewards Across FICO Score Percentiles by Reward Type. This figure illustrates the dollar magnitude of average net rewards on reward cards across the FICO distribution by reward type. The red line plots the average net reward for borrowers with an annual income below 44 thousand, the yellow 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 net reward (in dollar) 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.

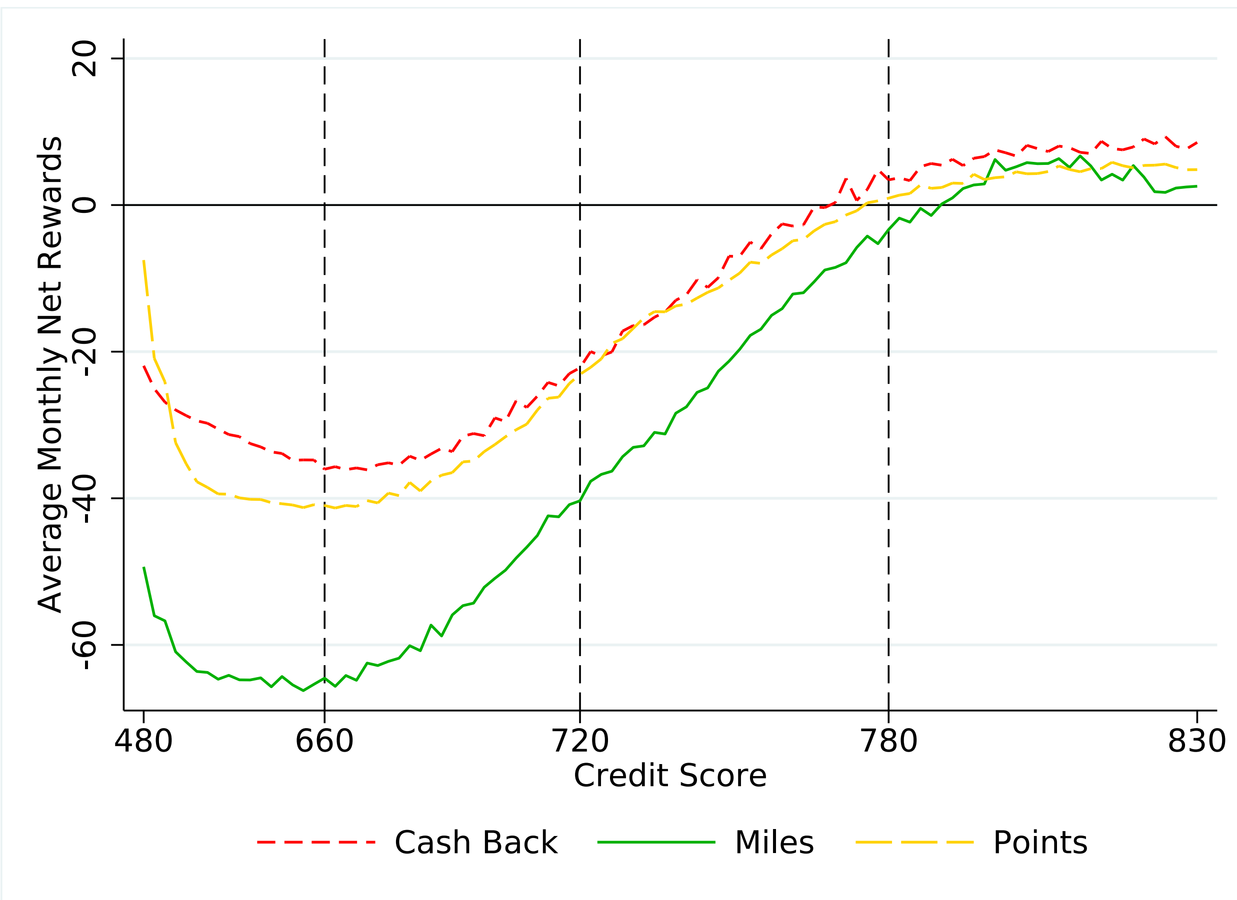


Figure A3. Fee Charges Across FICO Score Percentiles. This figure illustrates the dollar magnitude of average fee charges across the FICO distribution, separately for reward cards (solid red line) and classic cards (dashed blue line). For each card type, we plot the average fee charge for 100 equal-sized 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.

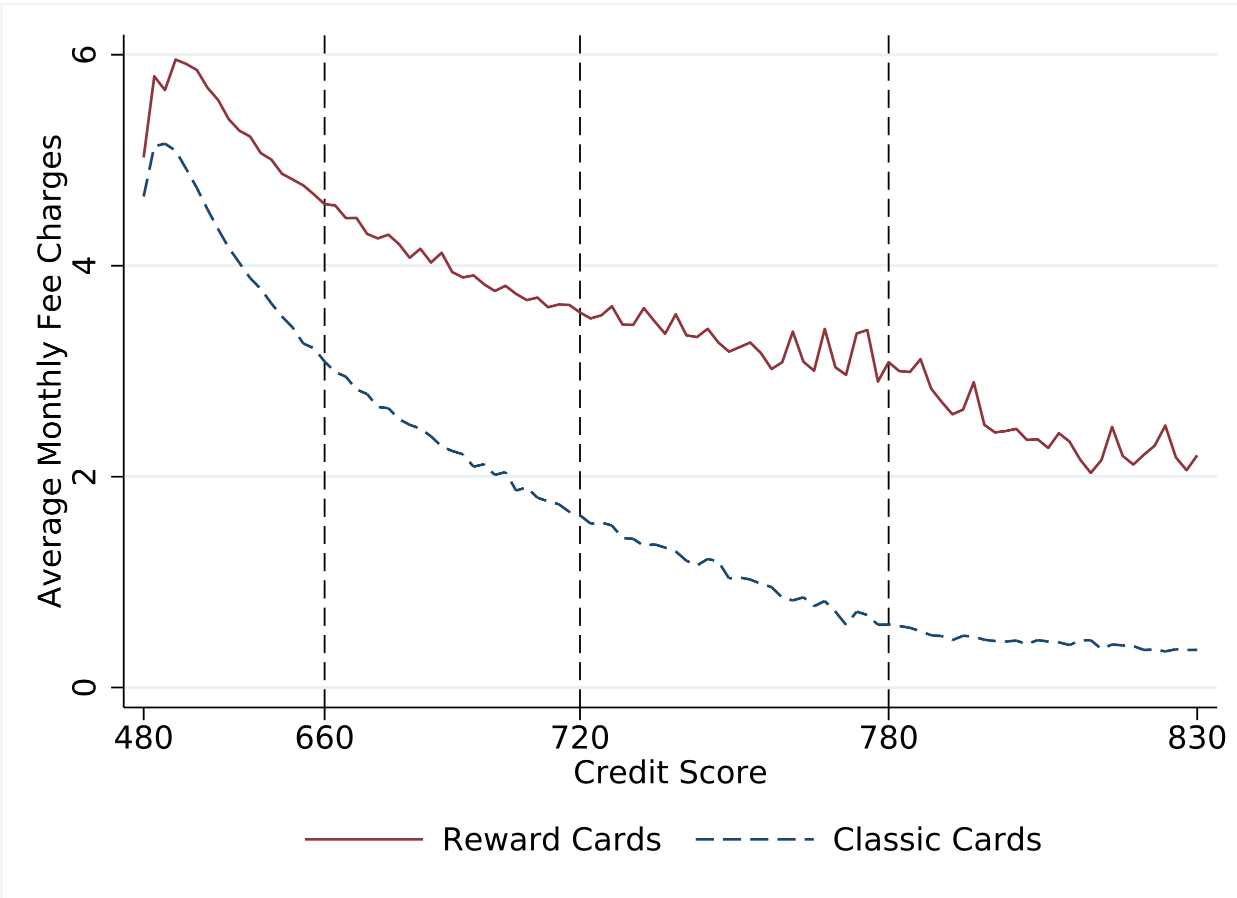


Figure A4. FICO Score Distributions by Income Groups. This figure illustrates the distribution of FICO scores across the full sample (solid red line) and three different income groups: low-income cardholders with an annual income below $44 thousand; middle-income cardholders with an annual income between $44-79 thousand; and high-income cardholders with an annual income above $79 thousand. The 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.

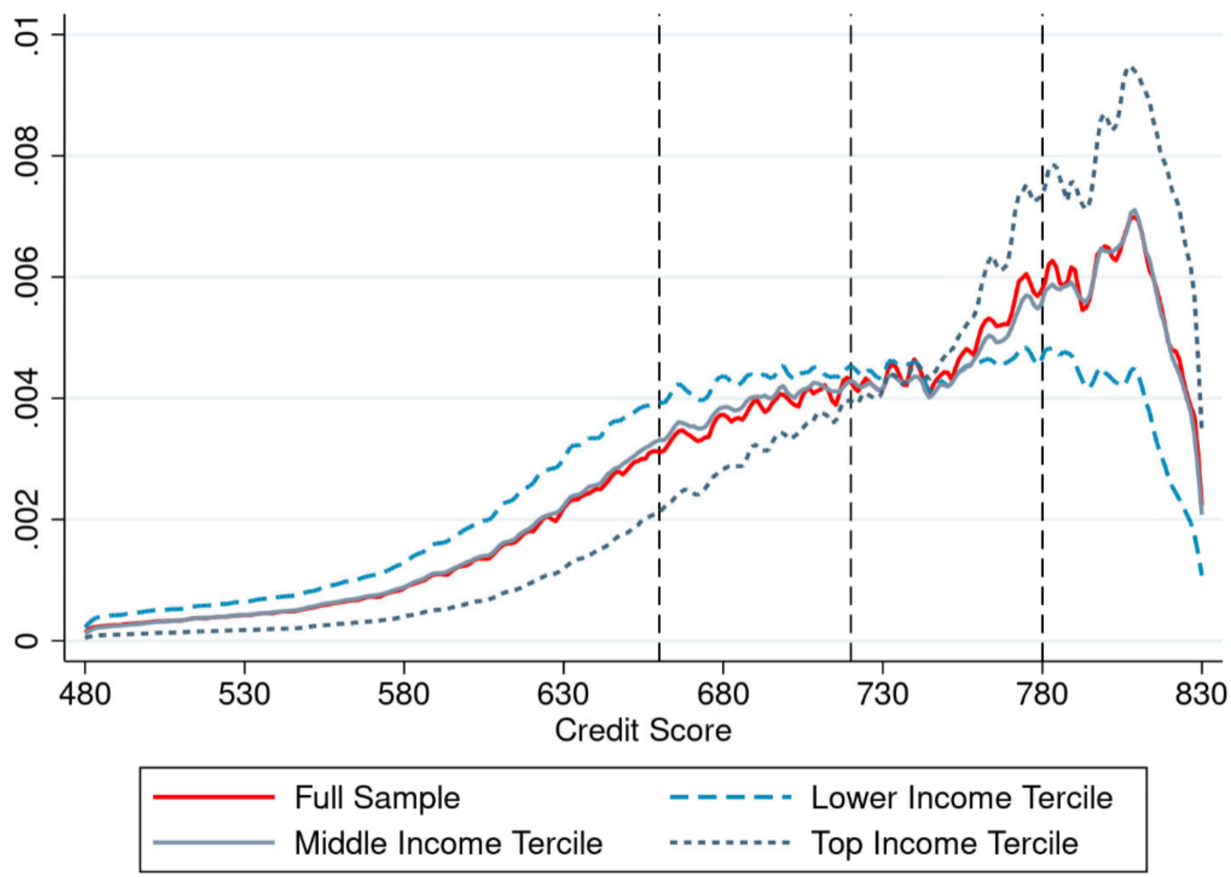
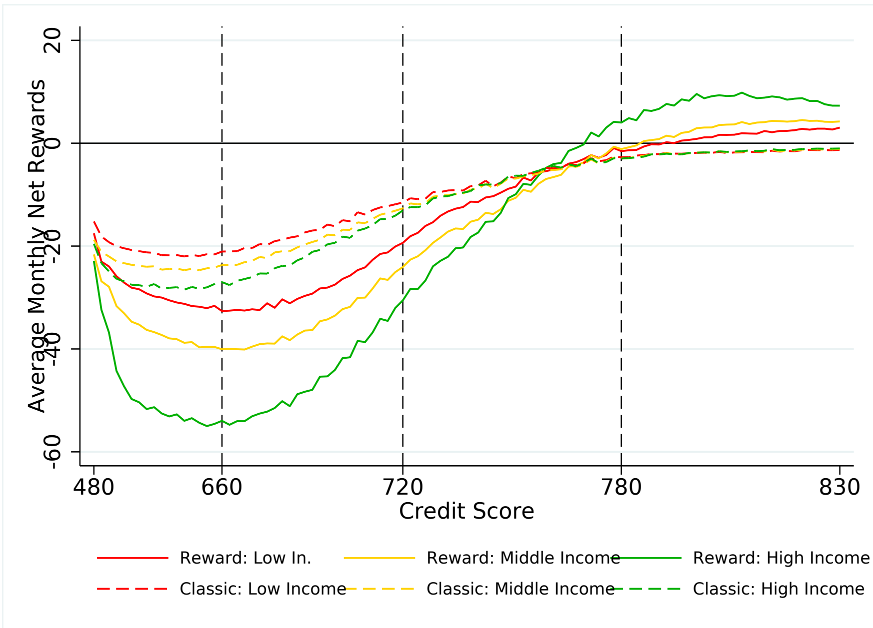


Figure A5. Net Rewards Across the FICO Distribution by Income. Panel A plots the dollar magnitude of average net rewards across the FICO distribution, separately for reward cards (solid lines) and classic cards (dashed lines), and for three different income groups (below 44 thousand, 44 thousand and 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 Classic Cards



(B) Coefficient Plot

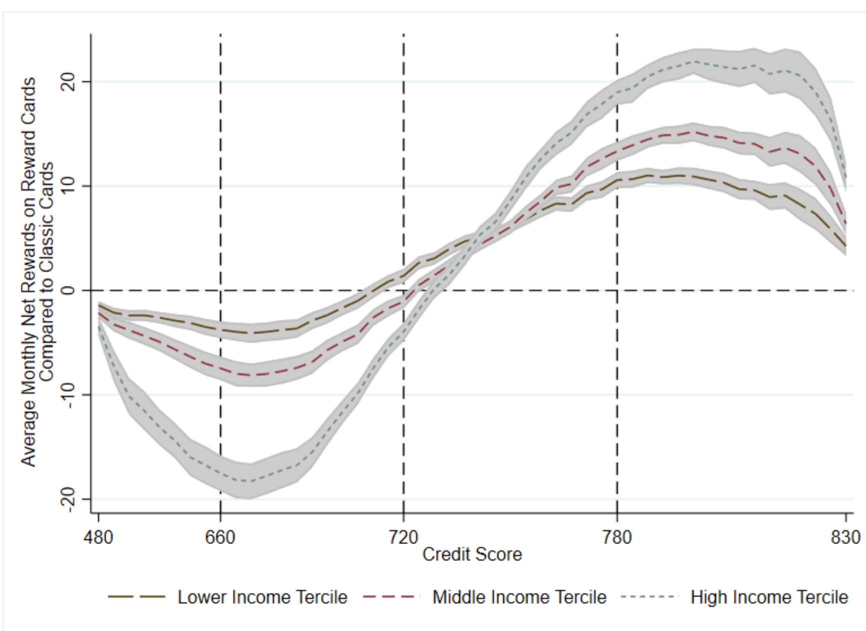


Figure A6. Net Rewards Across Income Percentiles. This figure illustrates the dollar magnitude of average net rewards across the income distribution, separately for reward cards (solid red line) and classic cards (dashed blue line). For each card type, we plot the average net reward for 100 equal-sized 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.

D. Additional Tables

Table A1. Aggregate Net Rewards

This table presents the aggregate sum of net rewards (in USD million) 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). The table is based on our sample of 91 million reward cards in March 2019.

	Negative Rewards (1)	Positive Rewards (2)	Δ (3)
All Reward Cards	-4140	1260	-2880
Sub-Prime	-1030	35	-996
Near-Prime	-1630	134	-1496
Prime	-1130	407	-723
Super-Prime	-361	680	319

Table A2. 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 III.A. Our 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

Table A3. Fee Components

This table presents the estimation results for differences in annual fee, late payment fee, and other fee charges between reward cards and classic cards from Equation (2) in Section IV.A:

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

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 characteristics include the credit limit, amount past due, card age, a joint account indicator, and a fraud dummy. Borrower characteristics including a deposit relationship indicator, a lending relationship dummy, the total number of cards the consumer has with the bank, a workout program dummy, and a bankruptcy indicator. Borrower income and FICO are defined as of March 2018 i.e., one year prior. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Annual Fee Charges		Late Payment Fee Charges		Other Fee Charges	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	0.51***		0.14***		0.06***	
	(0.05)		(0.03)		(0.02)	
Reward Card × Sub-Prime		0.56***		0.14*		0.08***
		(0.04)		(0.08)		(0.02)
Reward Card × Near-Prime		0.35***		0.19***		0.24***
		(0.07)		(0.04)		(0.03)
Reward Card × Prime		0.57***		0.15***		0.05*
		(0.06)		(0.02)		(0.03)
Reward Card × Super-Prime		0.54***		0.08***		-0.12***
		(0.05)		(0.01)		(0.02)
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	237,573,278	237,573,278	237,573,278	237,573,278	237,573,278	237,573,278

Table A4. Net Rewards by Income Groups—Top Income Distribution

This table presents the estimation results for differences in net rewards between reward cards and classic cards from Equation (2) in Section IV.A:

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

We reports results separately for three different annual income groups. 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 characteristics include the credit limit, amount past due, card age, a joint account indicator, and a fraud dummy. Borrower characteristics including a deposit relationship indicator, a lending relationship dummy, the total number of cards the consumer has with the bank, a workout program dummy, and a bankruptcy indicator. Borrower income and FICO are defined as of March 2018 i.e., one year prior. 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 A5. Net Rewards by Type of Reward Card

This table presents the estimation results for differences in net rewards between reward cards and classic cards from Equation (2) in Section IV.A:

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

We reports results separately for the three types of reward cards i.e., miles, cash back, 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 classic 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 characteristics include the credit limit, amount past due, card age, a joint account indicator, and a fraud dummy. Borrower characteristics including a deposit relationship indicator, a lending relationship dummy, the total number of cards the consumer has with the bank, a workout program dummy, and a bankruptcy indicator. Borrower income and FICO are defined as of March 2018 i.e., one year prior. Standard errors are clustered at the bank-state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Miles Cards		Cash Back 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: Bank × Zip × Income × FICO	Y	Y	Y	Y	Y	Y
Observations	113,283,147	113,283,147	153,206,808	153,206,808	158,481,157	158,481,157

Table A6. Overindebtedness: Difference-in-differences Analysis, Only Cards with a Bank-initiated Credit Line Increase

This table presents the estimation results for the difference-in-differences regression in Equation (3) in Section VI.A. 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 classic 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 only cards with 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. 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)
Mean Y	860.315		851.559		1922.45	
Card Controls (Pre-Period)	Y	Y	Y	Y	Y	Y
Cardholder Controls (Pre-Period)	Y	Y	Y	Y	Y	Y
Income and FICO (Pre-Period)	Y	Y	Y	Y	Y	Y
Spending and Payments (Pre-Period)	Y	Y	Y	Y	Y	Y
FE: Bank × Zip	Y	Y	Y	Y	Y	Y
Observations	1,236,604	1,236,604	1,236,604	1,236,604	1,236,604	1,236,604

Table A7. Share of Misallocated Payments—Two-card Sample

This table presents the estimation results for differences in the share of misallocated payments (as defined in Equation A5 in Section B) between reward cards and classic cards from Equation (2) in Section IV.A. The analysis 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:						
At least two cards with revolving debt at the same bank	Y	Y	Y	Y	Y	Y
Not fully paid balance on all cards with revolving debt	Y	Y	Y	Y	Y	Y
Minimum payment on all cards with revolving debt and more than the minimum on at least one	N	N	Y	Y	Y	Y
Different APRs on all cards with revolving debt	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