Who Pays For Your Rewards?

Cross-Subsidization in the Credit Card Market

Sumit Agarwal   Andrea F. Presbitero   André F. Silva   Carlo Wix[1]

Preliminary draft - May 2022

Abstract

We study credit card rewards as an ideal laboratory to quantify the cross-subsidy from naive to sophisticated consumers in retail financial markets. Using granular data on the near universe of credit card accounts in the United States, we find that sophisticated consumers profit from reward credit cards at the expense of naive consumers who lose money both in absolute terms and relative to classic cards. We estimate an aggregate annual cross-subsidy of $15.5 billion. Notably, our results are not driven by income—while sophisticated high-income consumers benefit the most, naive high-income consumers pay the most. Banks lure consumers into the use of reward cards by offering lower interest rates than on comparable classic cards and bank profits are highest for borrowers in the middle of the credit score distribution. We show that credit card rewards transfer wealth from less to more educated, from poorer to richer, from rural to urban, and from high to low minority areas, thereby widening existing spatial disparities.

[1]Sumit Agarwal is at the National University of Singapore. Andrea F. Presbitero is at the International Monetary Fund and CEPR. André F. Silva and Carlo Wix are at the Federal Reserve Board. For helpful comments and suggestions, we would like to thank Paolina Medina (discussant), Luciana Orozco (discussant), Daniel Paravisini, and the conference and seminar participants at the 5th Bristol Workshop on Banking and Financial Intermediation, the 2022 UBC Winter Finance Conference (Whistler), the Federal Reserve Board, and the International Monetary Fund. The views expressed in this paper solely reflect those of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System, the International Monetary Fund, nor of anyone else associated with these institutions.

Electronic copy available at: https://ssrn.com/abstract=4126641

I. Introduction

When consumers lack financial sophistication, they often make costly mistakes (Campbell, 2006). In response, banks can design financial products to exploit these mistakes (DellaVigna and Malmendier, 2004; Heidhues and Kőszegi, 2010, 2017). These products often combine salient benefits with shrouded, back-loaded payments. Naive consumers might underestimate these payments and thus 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 cross-subsidy from naive to sophisticated consumers (Gabaix and Laibson, 2006) and thereby contribute to inequality (**?**Lusardi, Michaud, and Mitchell, 2017).

Empirically quantifying the extent of such cross-subsidization is, however, challenging. First, for many financial products such as mortgages, optimal behavior depends on consumers' risk aversion, expectations about economic developments, and other hard-to-measure variables (Campbell and Cocco, 2003; Fisher et al., 2021; Guiso et al., 2021). To determine what constitutes biased behavior is therefore not straightforward. Second, linking the cross-subsidy to borrower characteristics requires detailed individual-level data on the costs and benefits of using a financial product, whereas especially the latter are often unobservable or at least hard to quantify.

In this paper, we use credit card rewards as an ideal laboratory to study the cross-subsidy from naive to sophisticated 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 the U.S. consumer credit card market. Reward cards account for over 80 percent of total credit card spending and for over 60 percent of all new credit card originations (CFPB, 2019). In 2019, the largest U.S. banks paid out $35 billion in credit card rewards. Thus, while consumers pay for the use of credit cards through interest payments and fees, they can also earn money through rewards. These costs and benefits are likely not

Electronic copy available at: https://ssrn.com/abstract=4126641

equally distributed across cardholders, with some consumers paying for and others earning money from credit card usage.

We use comprehensive credit card data from the Federal Reserve Board's Y-14M reports which encompass the near-universe of accounts in the United States. The dataset contains monthly account-level information on, inter alia, cardholders' purchase volumes, outstanding balances, interest and fee payments, borrowers' income and FICO scores, as well as their accumulated rewards. We use these variables to calculate a cardholders' monthly net reward, defined as the dollar value received in rewards minus interest and fee payments.

We compare the outcomes of reward cards and classic cards across the FICO score distribution.[1] FICO scores are designed to capture borrowers' creditworthiness and measure their likelihood to repay debt on time. As FICO scores are largely based on a borrower's payment history and their outstanding debt relative to available credit, they capture the same type of credit card behavior that is associated with a lack of financial sophistication, namely over-borrowing (Meier and Sprenger, 2010; Gathergood, 2012), higher fee payments (Stango and Zinman, 2014), and suboptimal repayment behavior (Kuchler and Pagel, 2021). In our baseline analysis, we therefore use FICO scores as a proxy measure of financial sophistication.[2]

We first quantify the cross-subsidy from naive to sophisticated borrowers induced by reward credit cards. For sub-prime (with a FICO score below 660) and near-prime (660 to 720) borrowers, monthly net rewards are on average \$5.1 lower on reward cards relative to similar classic cards. For prime (720 to 780) and super-prime (above 780) borrowers, monthly net rewards are on average \$11.7 and \$21.4 higher, respectively. This result is driven by both the cost and the benefit margin of net rewards. Super-prime borrowers earn on average \$11.6 in rewards and pay \$10.5 less in interest on reward cards than on classic

[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 do not earn any form of rewards.

[2]See Agarwal, Rosen, and Yao (2016), Amromin, Huang, Sialm, and Zhong (2018), and Bhutta, Fuster, and Hizmo (2021) for previous literature using FICO scores as a measure for financial sophistication. We further show that FICO scores are strongly correlated with mistake-based measures of financial sophistication, as suggested by Calvet, Campbell, and Sodini (2009).

Electronic copy available at: https://ssrn.com/abstract=4126641

cards. In contrast, sub-prime borrowers earn only $1.8 in rewards but pay $6.1 more in interest. Thus, high FICO borrowers on average earn money with the use of reward cards while low FICO borrowers on average lose money. In aggregate terms, we find an annual cross-subsidy of $15.5 billion induced by credit card rewards.

Our results could conceivably be driven by income instead of financial sophistication. FICO scores might be positively correlated with income and high-income consumers might spend more money, which allows them to earn higher rewards. In fact, credit card rewards are often framed as a "reverse Robin Hood" mechanism in which the poor subsidize the rich.[3] Our further results, however, show that this explanation is at best incomplete. We find that the cross-subsidy from naive to sophisticated consumers takes place in all income groups. While sophisticated high-income borrowers benefit the most from reward credit cards, naive high-income borrowers on average pay the most. For sub-prime and near-prime borrowers with high income (above $85,000), net rewards are on average $15.0 and $12.2 lower on reward cards than on classic cards. Meanwhile, for sub-prime and near-prime borrowers with low income (below $50,000), net rewards are only $2.0 and $0.8 lower. Thus, sophisticated high-income borrowers benefit from reward credit cards largely at the expense of naive high-income borrowers.

The cross-subsidy is largely driven by the higher interest charges of low FICO borrowers, which could either be due to higher outstanding balances or due to higher interest rates on reward cards. We find outstanding balances to be the relevant margin. Sub-prime and near-prime borrowers carry a substantially higher balance on reward cards compared to classic cards, yielding higher interest charges. Both high and low FICO borrowers spend more money on reward than on classic cards, but only sophisticated borrowers pay their balances back on time. Reward cards therefore exploit the over-borrowing (Meier and Sprenger, 2010) and suboptimal repayment behavior (Kuchler and Pagel, 2021) of naive consumers.

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

Electronic copy available at: https://ssrn.com/abstract=4126641

While FICO scores have previously been used in the literature as a proxy for financial sophistication (Agarwal, Rosen, and Yao, 2016; Amromin, Huang, Sialm, and Zhong, 2018; Bhutta, Fuster, and Hizmo, 2021), other papers have suggested to measure consumers' financial sophistication based on the extent to which they make "financial mistakes" (Calvet, Campbell, and Sodini, 2009; Jørring, 2020). Focusing on borrowers 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 payments. 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. The share of misallocated payments is strongly decreasing in FICO scores. On average, the share is twice as high for low FICO than for high FICO borrowers, providing corroborating evidence that FICO scores are a reasonable proxy measure for financial sophistication.

Next, we turn to the supply side and study reward credit cards from the banks' perspective, investigating both pricing strategies and profits. Banks offer lower APRs on reward cards than on classic cards across the entire FICO distribution, suggesting that banks lure consumers into the use of reward cards. This interest rate differential is larger for high FICO borrowers than for low FICO borrowers. For sub-prime borrowers, APRs on reward cards are on average 0.8 percentage points lower than on classic cards, while for super-prime borrowers reward card APRs are on average 2.7 percentage points lower. 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 and realized charge-offs.[4] We find that banks' profits from reward cards

[4]Banks' interchange income and realized charge-offs are variables which we do not consider in the analysis of borrowers' net rewards. As discussed in Section II.A, when consumers pay with credit cards, banks charge an interchange fee from the merchant acquirer which is usually passed through to the merchant.

Electronic copy available at: https://ssrn.com/abstract=4126641

are highest for near-prime and prime borrowers in the middle of the FICO distribution. We further document substantial differences regarding banks' source of revenue between high and low FICO borrowers in the credit card market. For sub-prime borrowers, more than 60 percent of banks' revenues stem from interest income, while for super-prime borrowers, up to 80 percent stem from interchange income.

Finally, we study the geographic distribution of net rewards across ZIP codes and investigate whether the wealth transfer induced by credit card rewards is correlated with socio-economic variables. We find that average net rewards are higher in ZIP codes with a more educated population, higher income, a higher population density, and a lower share of minority residents. Credit card rewards therefore transfer wealth from less to more educated, from poorer to richer, from rural to urban, and from high to low minority areas, thereby widening existing spatial disparities.

Our contribution to the literature is twofold. First, we empirically quantify the cross-subsidy from naive to sophisticated consumers, which has, thus far, 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 naive consumers by charging back-loaded fees. In Gabaix and Laibson (2006) and Heidhues and Kőszegi (2017), products with such pricing schemes benefit sophisticated consumers at the expense of naive consumers and the latter cross-subsidize the former. Two recent papers empirically study such cross-subsidies in the context of the mortgage market. For Italy, Guiso et al. (2021) report a subsidy from naive to sophisticated households of 303 euros per year, induced by banks steering naive households towards sub-optimal mortgages. For the United Kingdom, Fisher et al. (2021) find that counterfactual mortgage rates without cross-subsidization would be 20 basis points higher than the teaser rates which benefit sophisticated households. Both empirical studies are based on structural models of households' mortgage choices, thereby requiring assumptions about a household's utility derived from housing, risk aversion, expectations about economic developments, and

Electronic copy available at: https://ssrn.com/abstract=4126641

other hard-to-measure parameters (Campbell and Cocco, 2003). In contrast, our empirical setting and our unique data set allow us to readily quantify the costs (interest and fee payments) and benefits (rewards) in monetary terms, thereby allowing for a straightforward calculation of the cross-subsidy from naive to sophisticated borrowers.

Second, we contribute to the literature on reward credit cards. The existing literature thus far has largely focused on interchange fees as a source of funding for credit card rewards.[5] 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 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 cross-subsidy from cash users 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 cross-subsidy from cash to credit card users and find that they imply a transfer from low-income to high-income consumers. In contrast, our study focuses on the cross-subsidy within credit card users, which is, as we argue, the more important margin. We show that the relevant wealth transfer is from naive to sophisticated consumers and not across income cohorts.

II. Background

A. Credit Card Rewards and Cross-Subsidization

Credit card rewards—in the form of cashback, miles, or points—are loyalty programs by banks which offer various benefits to cardholders per dollar spent on the credit card. Cashback cards refund a small percentage amount of the net purchase volume (usually between 0.5 and 3 percent), while miles and points cards let cardholders accrue bonus points that can be redeemed at frequent flyer programs (miles cards) or, more generally, at partnering

[5] We describe the market for credit card rewards in detail in Section II.A.

Electronic copy available at: https://ssrn.com/abstract=4126641

airlines, hotels, or retailers (points cards). Reward credit cards are a ubiquitous and increasingly important aspect of consumer finance, accounting for over 80 percent of total credit card spending and over 60 percent of all new credit card originations in the United States (CFPB, 2019). In 2019, the largest U.S. banks paid out $34.8 billion in aggregate credit card 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.[6] Following Felt, Hayashi, Stavins, and Welte (2020), consider the example of a cardholder making a $100 purchase with a reward credit card. This payment initially flows from the cardholder to the card-issuing bank, which in turn rewards the cardholder with, for instance, $1 in cashback, miles, or points. The card issuer then retains a $2 interchange fee and sends the remaining $98 to the merchant acquirer, which in turn pays a $0.15 network fee to the card network. The merchant acquirer subsequently sends $97.70 to the merchant, not only passing through interchange and network fees, but also additionally charging a merchant service charge ($0.15). Thus, merchants only receive a fraction of the initial purchase amount and potentially respond by increasing retail prices for everyone. Therefore, 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. Much of the existing literature has therefore focused on the cross-subsidization of reward credit cardholders by cash and debit card users (Schuh, Shy, and Stavins, 2010; Felt, Hayashi, Stavins, and Welte, 2020).

Another source of funding for credit card rewards, however, are fees (such as late and overlimit fees) and interest payments from credit cardholders with unpaid outstanding bal-

[6]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.

Electronic copy available at: https://ssrn.com/abstract=4126641

ances. 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 which are passed through to merchants. We therefore consider the cross-subsidy within credit card users to be more important than the transfer from cash to card users and focus on the cross-subsidization of reward programs within the credit card market.

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 wealth 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.

B. Financial Sophistication and Consumer Credit

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. Naive consumers are unaware of their time-inconsistent, present-biased preferences and, as a result, susceptible to using financial products with salient benefits and shrouded, back-loaded fees (O'Donoghue and Rabin, 2001; Heidhues and Kőszegi, 2010). In the context of consumer credit, a lack of financial sophistication is associated with over-indebtedness

Electronic copy available at: https://ssrn.com/abstract=4126641

(Meier and Sprenger, 2010; Gathergood, 2012), higher fee payments (Stango and Zinman, 2014), and suboptimal repayment behavior (Kuchler and Pagel, 2021).

In response, profit-maximizing banks can offer retail financial products designed to exploit these biases (DellaVigna and Malmendier, 2004; Heidhues and Kőszegi, 2017). Rewards credit cards constitute an important example. While banks prominently advertise the rewards that can be earned with credit cards, they do not saliently display the costs associated with interest and fee payments. As a result, especially naive consumers are often unaware of their credit card terms and the financial consequences associated with high credit card debt (Disney and Gathergood, 2013; Lusardi and Tufano, 2015). In contrast, sophisticated consumers are less likely to incur interest and fee payments. They can thus reap the rewards while avoiding the costs and earn money through credit card usage. Credit card rewards can therefore constitute a cross-subsidy from naive to sophisticated consumers, akin to Gabaix and Laibson (2006).

The financial behavior of consumers is reflected in their credit scores. Credit Scores are standardized, numerical indicators that are designed to capture borrowers' creditworthiness and measure their likelihood to repay debt on time. The most common credit score is the FICO score developed by the Fair Isaac Corporation. FICO scores are largely based on a borrower's payment history and their outstanding debt relative to available credit.[7] Consequently, borrowers with higher (lower) FICO scores 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 over-indebtedness and suboptimal repayment behavior.

In our baseline analysis, we hence use FICO scores as a proxy measure of financial sophistication.[8] In Section VI, we further document that FICO scores are strongly correlated

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

[8]For further papers using FICO scores as a measure for financial sophistication, see Agarwal, Rosen, and Yao (2016); Amromin, Huang, Sialm, and Zhong (2018); and Bhutta, Fuster, and Hizmo (2021).

Electronic copy available at: https://ssrn.com/abstract=4126641

with mistake-based measures of financial sophistication, as suggested by Calvet, Campbell, and Sodini (2009). Following Ponce, Seira, and Zamarripa (2017) and Gathergood, Mahoney, Stewart, and Weber (2019), we calculate the share of misallocated payments and purchases for borrowers with multiple credit cards and show that these shares are highly predictive for borrowers' FICO scores.

III. 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 analysis focuses on the cross section of all credit cards in March 2019.[9] We focus on general purpose and private label, unsecured, consumer credit cards with a revolving feature. We further exclude corporate credit cards and accounts which are either closed or inactive, with no credit or balance activity in the last twelve months. This sample construction procedure results in sample of about 166 million credit cards as of March 2019.

[9]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).

Electronic copy available at: https://ssrn.com/abstract=4126641

IV. Methodology and Summary Statistics

A. *Estimating Monthly Net Rewards*

While reward credit cards allow consumers to earn money through the use of their 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 gross rewards earned on the card during the same period:

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

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

$$\text{Cumulative Rewards}_{i,t} = \text{Cumulative Rewards}_{i,t-1} + \text{Gross Rewards}_{i,t} - \text{Redemptions}_{i,t} \tag{2}$$

We observe the stock variable *Cumulative Rewards*, but not the flow variables *Gross Rewards* or *Redemptions*. To calculate the monthly net rewards in Equation (1), we estimate the monthly variable *Gross Rewards* using the following methodology: 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:

$$\text{Card-Specific Reward Rate}_{i,t} = \frac{\Delta\text{Cumulative Rewards}_{i,t}}{\text{Purchase Volume}_{i,t}} \tag{3}$$

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

Electronic copy available at: https://ssrn.com/abstract=4126641

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.[10] Within each cluster, we then 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 this estimated reward rate to calculate the monthly gross rewards of card i in month t as follows:[11]

$$\text{Gross Rewards}_{i,t} = \text{Estimated Reward Rate}_{i,t} \times \text{Purchase Volume}_{i,t} \tag{4}$$

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 gross rewards from Equation (4) allows us to calculate the monthly net rewards of card i in month t as defined in Equation (1).

B. *Econometric Model*

We study the extent to which credit card rewards constitute a cross-subsidy from naive to sophisticated consumers and what drives this cross-subsidy. To this end, we compare credit card outcomes between reward cards and classic cards with similar card- and borrower

[10]This procedure yields 380 individual credit card product cluster. Table A1 in the appendix describes in detail all variables used in the calculation of the variable *Net Rewards*.

[11]In our raw sample, our 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 close to the $167 in annual rewards per account reported in CFPB (2019), thereby confirming the validity of our approach.

Electronic copy available at: https://ssrn.com/abstract=4126641

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:

$$\mathrm{Y}_{ibj} = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D_j^F\right) + \alpha_{b,z,w,f} + \sum_m X_i^m + \sum_n Z_j^n + \varepsilon_{ibj} \tag{5}$$

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 borrowers (with a FICO score below 660), near-prime borrowers (600-720), prime borrowers (720-780), and super-prime borrowers (above 780), respectively. $\alpha_{b,z,w,f}$ are interacted fixed effects at the bank × ZIP code × income percentile × 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 age of card in months, a promotion dummy which takes the value of 1 if the account is under promotion and 0 otherwise, and a joint account dummy which takes on the value of 1 if the account has more than one primary obligor and 0 otherwise. We further control for the following borrower-level characteristics Z: a relationship dummy which takes on the value of 1 if the borrower has another non-credit card banking relationship with the same bank and a bankruptcy dummy which takes on the value of 1 if the borrower has completed or is in an ongoing bankruptcy process.

Our dataset further contains a unique borrower identifier within banks which allows us to compare credit card outcomes between reward and classic cards within the same borrower j. For this specification, we restrict our sample to the set of borrowers who own at least one reward card and one classic card within the same bank b and include borrower fixed effects η_j to estimate the following regression specification:

$$\mathrm{Y}_{ibj} = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D_j^F\right) + \eta_j + \sum_m X_i^m + \varepsilon_{ibj} \tag{6}$$

Electronic copy available at: https://ssrn.com/abstract=4126641

As we are now comparing outcomes within the same borrower, this specification absorbs the fixed effects α as well as the borrower-specific control variables Z from Equation (5). All other variables are defined as before. Our dataset, however, does not allow us to identify borrowers across banks and the analysis is therefore subject to the caveat that these borrowers might hold additional credit cards at other banks. In particular, while the comparison within-borrower has the clear advantage of controlling for all unobservable borrower heterogeneity (like differences in tastes and preferences), it ignores the potential spillover effects that other (reward or classic) credit cards could have on the spending and repayment on the observed cards.

C. Summary Statistics

Table I presents card-level summary statistics as of March 2019 for all cards in our sample, separately for reward cards and classic cards, and for the sample of borrowers with multiple cards within the same bank. Panel A presents variables related to the calculation of net rewards as described in Section IV.A. As shown in the first row, 55 percent of the cards in our sample are reward cards and 45 percent classic cards. The average reward card earns \$11.1 in monthly (gross) rewards and the average classic card—by definition—zero. However, reward cards also exhibit higher interest payments (\$20.8) than classic cards (\$14.1) and higher fee payments (\$3.9 versus \$2.8). Thus, in total, the average reward card yields a negative net reward of -\$13.7 and is therefore only slightly more "profitable" than the average classic card with a negative net reward of -\$16.8.

[Table I about here]

Panel B presents other credit card outcome variables. On average, reward cards exhibit significantly higher purchase volumes and outstanding balances and thus higher usage statistics than classic cards. Moreover, reward cards have substantially lower APRs than classic cards (19.9 versus 24.6) and substantially higher credit limits (\$10.6 thousand versus \$4.3

Electronic copy available at: https://ssrn.com/abstract=4126641

thousand). 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 borrowers who choose to use reward cards and classic cards, respectively.

As shown in Panel C, cardholders of reward cards have, on average, higher FICO scores than cardholders of classic cards (745.6 versus 702.5) and earn a higher annual income ($109.6 thousand vs. $78.1 thousand). These borrower-level differences could, in principle, explain why reward cards exhibit both a higher usage and lower APRs than classic cards, as shown in Panel B. The remainder of Panel C provides further summary statistics for the control variables of our regression methodology.

Column 6 reports the mean values for our sub-sample of 34 million credit cards held by borrowers with multiple cards at the same bank. Compared to the whole sample, borrowers with multiple cards have both lower gross rewards and higher interest charges, resulting in larger negative net rewards (-$20.8). In the sample of borrowers with multiple cards the share of reward cards is lower than in the whole sample and, as a result, borrowers have lower FICO scores and earn a lower income.

V. Cross-Subsidization in the Credit Card Market

A. Net Rewards

Figure 1 illustrates the magnitude of net rewards across the FICO distribution. For both reward cards and classic cards, average net rewards are increasing in FICO scores, suggesting that naive 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.[12] For these consumers, the monetary benefits of reward cards

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

Electronic copy available at: https://ssrn.com/abstract=4126641

outstrip their costs and, therefore, they earn money with the use of reward cards. 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 -$45 for reward cards and -$25 for classic cards. Thus, unsophisticated consumers on average lose money with their reward cards, both in absolute dollar terms and relative to classic cards.

[Figure 1 about here]

Figure 1 suggests that credit card rewards constitute a cross-subsidy from naive to sophisticated consumers. This descriptive pattern, however, might be driven by differences between borrowers with low and high FICO scores, regardless of whether they use reward or classic cards. Columns 1 to 3 of Table II present the estimation results for differences in net rewards between reward and classic cards of Equation (5) across all borrowers. All specifications include card- and borrower control variables. To make the comparison as homogeneous as possible in terms of borrower characteristics, we include, alternatively, bank × ZIP code × income percentile (Column 1), bank × ZIP code × FICO score percentile (Column 2), and bank × ZIP code × income percentile × FICO score percentile (Column 3) fixed effects. All three specifications show that net rewards are significantly higher for reward cards than for similar classic cards. The coefficient of the most conservative specification indicates that, on average, a reward card yields a $5.1 higher net reward than a classic card with similar features, issued by the same bank to a borrower with similar characteristics who lives in the same ZIP code and has a very similar FICO score and income.

[Table II about here]

These average net reward differentials between reward and classic cards, however, mask important differences between consumers across the FICO distribution. Column 4 reports the differences in net rewards between reward and classic cards, separately for sub-prime, near-prime, prime, and super-prime borrowers. Consistent with Figure 1, net rewards for

Electronic copy available at: https://ssrn.com/abstract=4126641

sub-prime and near-prime borrowers are on average \$5 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, \$11.7 and \$21.4 higher for prime and super-prime borrowers, respectively. Thus, while reward cards are more cost-effective than classic cards on average, only prime and super-prime borrowers gain from it, while unsophisticated consumers lose money by using reward cards and would be better off choosing classic cards.

Columns 5 and 6 present the estimation results for the sample of borrowers with multiple cards at the same bank, which allows us to compare the outcome of reward and classic cards *within the same borrower*. We obtain qualitatively and quantitatively similar results. In this specification, net rewards are \$1.6 higher for reward cards compared to similar classic cards. For sub-prime and near-prime borrowers, net rewards are on average \$5.8 and \$7.7 lower, and for prime and super-prime borrowers net rewards are on average \$6.7 and \$19.0 higher for reward cards than for similar classic cards.

In summary, Figure 1 and Table II show that credit card rewards constitute a cross-subsidy from naive to sophisticated consumers. To illustrate the aggregate size of this cross-subsidy, 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 group. The economic magnitude is substantial. As shown in Table III, 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.[13] This monthly cross-subsidy of \$1.3 billion translates into an annualized cross-subsidy of \$15.5 billion induced by reward credit cards. Of the \$4.1 billion that subsidize cardholders with positive net rewards, 1.1 billion come from sub-prime, 1.6 billion from near-prime, 1.1 billion from prime, and only 0.3 billion from super-prime cardholders. Of the \$1.3 billion earned by cardholders with positive net rewards, only \$36 million go to sub-prime, \$139 million to near-prime, \$367 million to prime, and \$751 million to super-prime cardholders. Thus, while sub-prime and near-prime borrowers are the largest

[13]The difference of \$2.8 billion constitutes bank income. We study the banks' perspective on reward credit card in Section VII.

Electronic copy available at: https://ssrn.com/abstract=4126641

source of funding for credit card rewards, prime and super-prime borrowers are the biggest beneficiaries. Reward credit cards therefore constitute a substantial aggregate wealth transfer from naive to sophisticated consumers.

[Table III about here]

B. Net Rewards Components

Figure 2 illustrates the magnitude of the three net reward components across the FICO distribution: gross rewards, interest charges, and total fee charges. For reward cards, average monthly gross rewards are increasing in FICO scores, ranging from below $5 for sub-prime borrowers, $5 to $9 for near-prime, $9 to $14 for prime, to around $15 for super-prime borrowers. For classic cards, gross rewards are zero by definition. Interest charges are hump-shaped in FICO scores and generally higher for reward cards than for classic cards. This difference is much larger for naive than for sophisticated borrowers. For near-prime borrowers, average interest charges are up to $20 higher for reward cards (around $40) than for classic cards (around $20), while for super-prime borrowers, average interest charges are around $5 for both reward cards and classic cards. Total fee charges are decreasing and L-shaped in FICO scores, ranging from up to $10 on average for sub-prime borrowers to less than $2 for super-prime borrowers, and are generally higher for reward cards than for classic cards.

[Figure 2 about here]

Table IV presents the estimation results of Equation (5) with gross rewards, interest charges, and total fee charges as outcome variables. As shown in Column 1, gross rewards are on average $7.0 higher on reward cards than on classic cards. Again, there is substantial heterogeneity across FICO groups as shown in Column 2. Gross rewards on reward cards are $1.8 higher for sub-prime borrowers, $5.5 higher for near-prime, $10.0 higher for prime, and $11.6 higher for super-prime borrowers. But sophisticated consumers do not only earn

Electronic copy available at: https://ssrn.com/abstract=4126641

more money in gross rewards, they also incur lower interest charges. For sub-prime and near-prime borrowers, interest charges are on average \$6.1 and \$9.9 higher on reward cards than on similar classic cards, while for prime and super-prime borrowers interest charges are on average \$2.3 and \$10.5 lower. Thus, sophisticated consumers do not only earn more rewards, they also pay less interest on reward than on classic cards. In contrast, interest charges exceed gross rewards for naive consumers, which therefore loose money with the use of reward cards.

[Table IV about here]

C. Net Rewards and Income

Our results that the net rewards of high FICO borrowers are cross-subsidized by low FICO borrowers could conceivably be driven by income instead of financial sophistication. FICO scores might be positively correlated with income and high-income consumers might spend more money, which allows them to earn higher rewards. 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).[14]

Our further 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 study net rewards across the FICO distribution within different income groups. Figure 3 illustrates the magnitude of net rewards across the FICO distribution for three different income groups. The red line plots the average net reward for borrowers with an annual income below \$50 thousand, the yellow line for borrowers with an annual income between \$50 thousand and \$85 thousand, and the green line for borrowers with an annual income above \$85 thousand. For super-prime borrowers, the distribution of average net rewards across income groups is consistent with a "reverse Robin Hood" hypothesis. High-income borrowers with high FICO scores benefit the most from reward credit cards compared

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

Electronic copy available at: https://ssrn.com/abstract=4126641

to mid- and low-income borrowers with high FICO scores. At the lower end of the FICO distribution however, this pattern is reversed and inconsistent with a "reverse Robin Hood" hypothesis. On average, net rewards are far more negative for high-income borrowers with low FICO scores than for mid- and low-income borrowers with low FICO scores.

[Figure 3 about here]

Table V shows that these patterns also hold in our regression analysis, when including granular fixed effects and controlling for card- and borrower-specific characteristics. High-income super-prime borrowers earn on average $27.9 in net rewards, while mid- and low-income super-prime borrowers earn on average $17.8 and $12.3, respectively. Consistent with Figure 3, their rewards are, however, also cross-subsidized by high-income borrowers. High-income sub-prime borrowers exhibit on average negative net rewards of -$15.0, while for mid- and low-income sub-prime borrowers, average net rewards are less negative with -$4.9 and -$2.0, respectively.

[Table V about here]

The combined results in Figure 3 and Table V show that, on average, sophisticated high-income borrowers benefit from reward credit cards largely at the expense of naive high-income borrowers.

D. Credit Card Usage

As discussed in Section V.B, the cross-subsidy from naive to sophisticated consumers is driven both by gross rewards, which are a function of a card's purchase volume, and interest payments, which are a function of a card's outstanding balances and interest rates. In this section, we therefore study differences in credit card usage between reward and classic cards across FICO scores.

Table VI presents the estimation results of Equation (5) with outstanding balances and purchase volumes as outcome variables. Across all consumers, purchase volumes are on

Electronic copy available at: https://ssrn.com/abstract=4126641

average \$307 higher on reward cards than on comparable classic cards. This differential is driven by sophisticated consumers. While sub-prime borrowers spend, on average, only \$5 more on their reward cards, super-prime borrowers spend \$598 more. This spending pattern across FICO groups, does, however not translate into credit card borrowing. While sub-prime and near-prime borrowers carry, on average, \$397 and \$755 higher outstanding balances on their reward cards, super-prime borrowers carry \$337 lower balances. Thus, even though sophisticated borrowers spend more money on their reward cards, they borrow less.

[Table VI about here]

VI. FICO Scores and Financial Sophistication

A recent stream of literature 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). In this section, we show that these mistakes are highly correlated with FICO scores, lending further support to their use as a proxy measure for financial sophistication. 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.

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 (MAP) share for borrower b on card i as the minimum between zero (if the actual payment is equal or lower than the optimal one)

Electronic copy available at: https://ssrn.com/abstract=4126641

and the difference between the optimal payment amount (OPA) and the actual payment amount (APA) scaled by the total payment amount:

$$\text{MAP Share} = \begin{cases} \frac{\text{Actual Payment Amount}_{i,b} - \text{Optimal Payment Amount}_{i,b}}{\text{Total Payment Amount}_{i,b}} & \text{if} \quad \text{APA}_{i,b} > \text{OPA}_{i,b} \\ 0 & \text{if} \quad \text{APA}_{i,b} \leq \text{OPA}_{i,b} \end{cases} \tag{7}$$

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 borrowers with low FICO scores misallocate up to 10 percent of all credit card repayments, the misallocated payment share is as low as 5 percent for borrowers with high FICO scores.

[Figure 4 about here]

We further study whether misallocated payments are higher on reward cards than on comparable classic cards. Table VII presents the estimation results of Equation (6) with the share of misallocated payments as the outcome variable. As shown in Column 1, the share of misallocated payments is 2 percentage points higher on reward cards. As shown in Column 2, this result is driven by borrowers with low FICO scores for which the share of misallocated payments on reward cards is higher than for prime- and super-prime borrowers.

[Table VII about here]

Finally, we provide evidence that FICO scores are also highly correlated with educational attainment across ZIP codes. Education has been shown to be highly correlated with financial sophistication (Campbell, 2006; Calvet, Campbell, and Sodini, 2009; Lusardi and Mitchell, 2014) and is therefore commonly used as a proxy measure (Calvet, Campbell, and Sodini, 2007; Agarwal, Ben-David, and Vincent, 2017). Figure 5 shows that the average FICO score across ZIP codes is strongly negatively correlated with low educational attainment as measured by the share of residents with a high school degree (but no more).

Electronic copy available at: https://ssrn.com/abstract=4126641

[Figure 5 about here]

Our combined results in Figure 4, Table VII, and Figure 5 show that FICO scores are highly correlated with financial mistakes at the card level and with education at the ZIP code level, thereby justifying our use of FICO scores as a proxy measure for financial sophistication.

VII. The Banks' Perspective: Pricing and Profits

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

A. Pricing

We first study the interest rates offered by banks on reward cards relative to comparable classic cards. Figure 6 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. This pattern is confirmed in the standard regression setting, estimating Equation (5) with APRs as the outcome variable. Columns 1 and 2 of Table VIII present the results. Across all borrowers, APRs on reward cards are, on average, 1.9 percentage points lower than on comparable classic cards. This interest rate differential between reward and classic cards is larger for high FICO than for low FICO borrowers. For sub-prime borrowers, banks on average offer 0.8 percentage points lower interest rates on reward cards, while for super-prime borrowers the difference is 2.7 percentage points. Taken together, this evidence would indicate that banks use aggressive pricing to lure consumers into the adoption of reward cards.

[Figure 6 about here]

[Table VIII about here]

Electronic copy available at: https://ssrn.com/abstract=4126641

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 for the bank. 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 the bank. To investigate more formally how the pricing strategy translate into bank profits, we define a bank's profit on credit card i as:

$$\text{Profit}_i = \text{Interest Paid}_i + \text{Total Fees}_i + \text{Interchange Income}_i \quad (8)$$

$$- \text{Gross Rewards}_i - \text{Realized Charge-Offs}_i \quad (9)$$

The variables *Interest Paid*, *Total Fees*, and *Gross Rewards* are defined as in Section IV. Whereas interest and fees represent payments from the borrower's perspective, they represent income from the bank's perspective. Conversely, whereas rewards represent income from the borrower's perspective, they represent costs from the bank's perspective. Our analysis of bank profitability also introduces two new variables which are not included in the previous analysis: *Interchange Income* and *Realized Charge-Offs*. As discussed in Section II.A, 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 follow Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015) and assess a bank's interchange income at the card level to be 2 percent of the purchase volume. 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 bank's balance sheet (CFPB, 2019). Our analysis so far excluded inactive or closed accounts as they have no further charging privileges and are therefore uninformative about borrowers' behavior. From a bank's perspective, however, realized charge-offs on closed accounts are an

Electronic copy available at: https://ssrn.com/abstract=4126641

important determinant of the ex-post profitability of an account. We therefore now include closed accounts in the analysis of banks' profits.

Columns 3 and 4 of Table VIII present the estimation results of Equation (5) with bank profits as the outcome variable. Across all borrowers, bank profits are about $4 higher on reward cards than on comparable classic cards. Again, these profits are not uniformly distributed across FICO scores. We find that bank profits per card are highest for near-prime and prime borrowers in the middle of the FICO distribution. For sub-prime borrowers, which tend to incur the highest charge-offs, profits are substantially lower for reward cards than for comparable classic cards. For super-prime borrowers, which tend to earn a lot of rewards but also incur low interest payments, bank profits are not significantly different for reward and classic cards. Thus, from the banks' perspective, near-prime and prime borrowers 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 7 illustrates the average revenue share of interest income, fee income, and interchange income as a percentage of total card revenue across the FICO distribution. For low FICO borrowers, banks revenues largely stem from interest income. For high FICO borrowers, 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 7 about here]

VIII. The Geography of Net Rewards

Our analysis so far focused on the cross-subsidy from naive to sophisticated consumers at the borrower level. In this section, we focus on the aggregate implications and analyze the reward-induced cross-subsidy across geographies in the United States.

Figure 8 plots the average net reward (Panel A) and the average FICO score (Panel B) across counties. The figure illustrates the high level of spatial correlation between the two

Electronic copy available at: https://ssrn.com/abstract=4126641

variables and confirm at the aggregate level the cross-subsidies from naive to sophisticated borrowers 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 8 about here]

A relevant concern is whether this transfer of resources is penalizing areas with specific socio-economic tracts, potentially widening spatial disparities. To answer this question we regress card-level net rewards on various ZIP code-level characteristics and estimate the following regression specification:

$$\text{Net Reward}_{i,z} = \sum_{k} \beta^k X_z^k + \varepsilon_{i,z} \tag{10}$$

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 household income; iii) population density per square kilometer; and iv) the percentage of residents who report their race as Black or African American.

As shown in Table IX, higher net rewards are associated with higher income and with a higher population density. Conversely, lower net rewards are associated with a lower level of education and with a higher share of black residents. These results suggest that rewards on credit cards are a potential channel that can exacerbate existing socio-economic disparities across regions in the United States, as they imply a transfer of resources from areas which are poorer, rural, less educated and with a higher share of Blacks or African Americans to those which are richer, urban, more educated and with a lower share of minorities. In particular, differences in education and and between rural and urban areas explain more than one third of the variation of net rewards across ZIP codes.

Electronic copy available at: https://ssrn.com/abstract=4126641

[Table IX about here]

IX. Conclusion

Credit card reward programs provide an ideal laboratory to study the cross-subsidy from naive to sophisticated consumers in retail financial markets. Using comprehensive and granular data from the Federal Reserve's Y-14M reports, we find that sophisticated consumers benefit from reward programs at the expense of naive consumers and estimate an annual cross-subsidy of of $15.5 billion. This cross-subsidy is driven by both the cost and the benefit margin of reward credit cards. Sophisticated 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, naive 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. Sophisticated high-income borrowers benefit the most from reward credit cards, but they do so at the expense of naive high-income borrowers. 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 further show that banks lure consumers into the use of reward cards by offering lower interest rates than on comparable classic cards. Banks profits from reward cards are highest for near-prime and prime borrowers in the middle of the FICO distribution.

We also document that the costs and benefits of credit card rewards are unequally distributed across geographies in the United States. Credit card rewards transfer wealth from less to more educated, from poorer to richer, from rural to urban, and from high to low minority areas, thereby widening existing spatial disparities.

Electronic copy available at: https://ssrn.com/abstract=4126641

REFERENCES

Agarwal, Sumit, Itzhak Ben-David, and Yao Vincent, 2017, Systematic mistakes in the mortgage market and lack of financial sophistication, *Journal of Financial Economics* 123, 42–58.

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.

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, 2007, Down or out: Assessing the welfare costs of household investment mistakes, *Journal of Political Economy* 115, 707–747.

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

Electronic copy available at: https://ssrn.com/abstract=4126641

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

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

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.

Disney, Richard, and John Gathergood, 2013, Financial literacy and consumer credit portfolios, *Journal of Banking & Finance* 37, 2246–2254.

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.

Electronic copy available at: https://ssrn.com/abstract=4126641

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.

Guiso, Luigi, Andrea Pozzi, Anton Tsoy, Leonardo Gambacorta, and Paolo Emilio Mistrullie, 2021, The cost of steering in financial markets: Evidence from the mortgage market, *Journal of Financial Economics* forthcoming.

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, 2020, Financial sophistication and consumer spending, *Mimeo* .

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.

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.

Electronic copy available at: https://ssrn.com/abstract=4126641

Lusardi, Annamaria, and Peter Tufano, 2015, Debt literacy, financial experiences, and overindebtedness, *Journal of Pension Economics & 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.

O'Donoghue, Ted, and Matthew Rabin, 2001, Choice and procrastination, *Quarterly Journal of Economics* 116, 121–160.

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

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.

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

Stango, Victor, and Jonathan Zinman, 2014, Limited and varying consumer attention: Evidence from shocks to the salience of bank overdraft fees, *Review of Financial Studies* 27, 990–1030.

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.

Electronic copy available at: https://ssrn.com/abstract=4126641

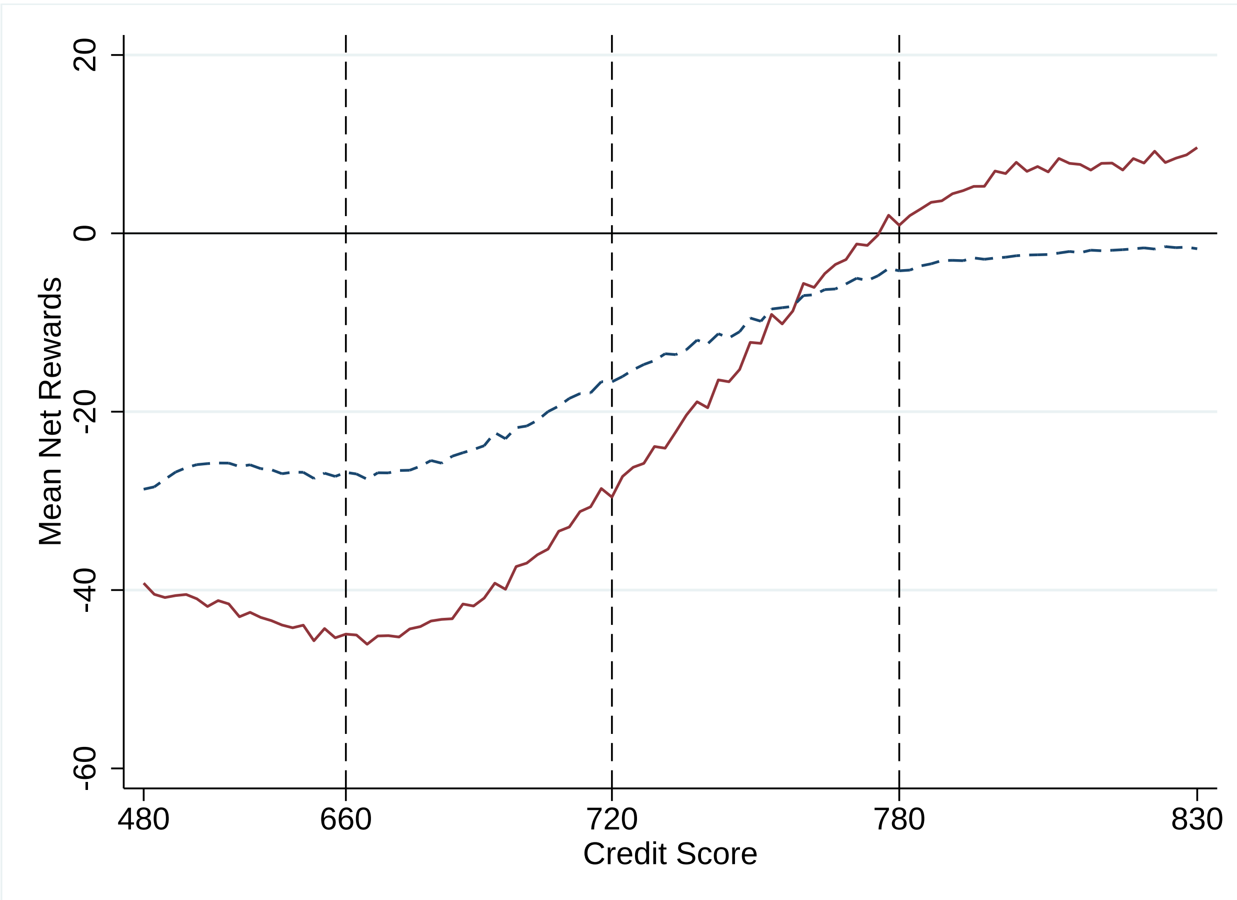
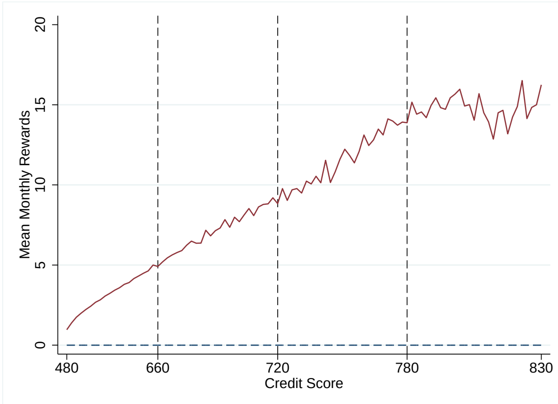


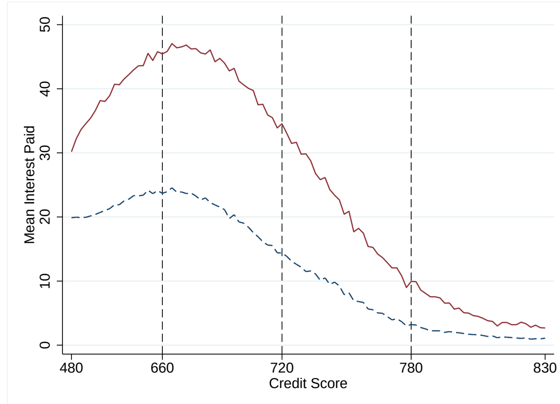
Figure 1. Net Rewards Across FICO Score Percentiles. This figure illustrates the magnitude of average net rewards across the FICO distribution, separately for reward cards (solid red line) and classic cards (dashed blue line). For each card type, we plot the average net reward for 100 equal-sized FICO 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 borrowers, respectively. The graph is based on our baseline sample of 166 million credit cards in March 2019.

Electronic copy available at: https://ssrn.com/abstract=4126641

(A) Gross Rewards



(B) Interest Charges



(C) Total Fee Charges

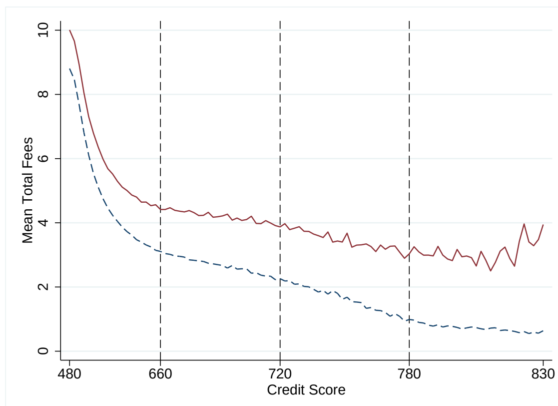


Figure 2. . This figure illustrates the dollar magnitude of average gross rewards (Panel A), interest charges (Panel B), and total fee charges (Panel C) across the FICO distribution, separately for reward cards (solid red line) and classic cards (dashed blue line). For each card type, we plot the average 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 borrowers, respectively. The graph is based on our baseline sample of 166 million credit cards in March 2019.

Electronic copy available at: https://ssrn.com/abstract=4126641

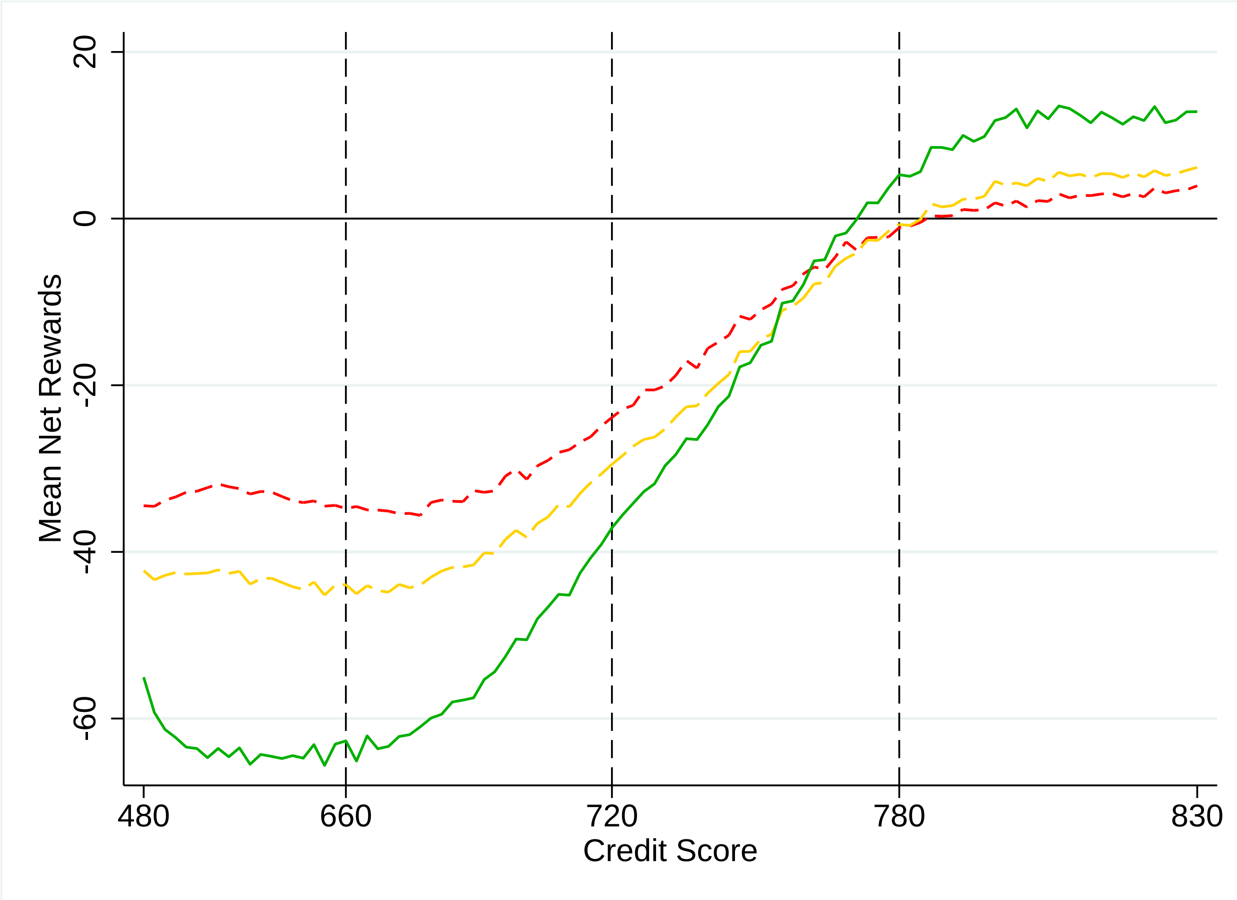


Figure 3. Net Rewards Across FICO Score Percentiles by Income Group. This figure illustrates the magnitude of average net rewards on reward cards across the FICO distribution by income group. The red line plots the average net reward for borrowers with an annual income below $50 thousand, the yellow line for borrowers with an annual income between $50 thousand and $85 thousand, and the green line for borrowers with an annual income above $85 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 borrowers, respectively. The graph is based on our sample of 91 million reward credit cards in March 2019.

Electronic copy available at: https://ssrn.com/abstract=4126641

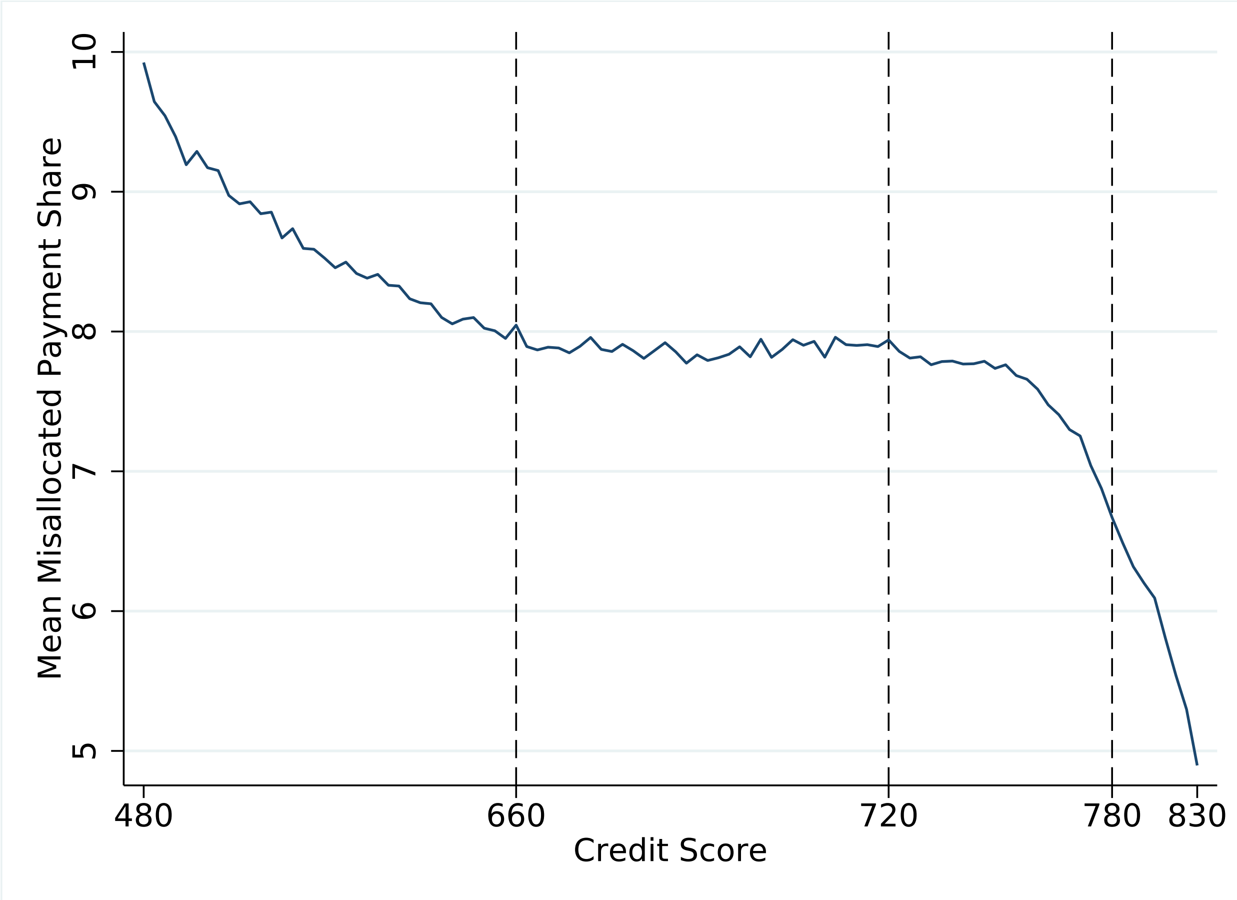


Figure 4. Share of Misallocated Payments Across FICO Score Percentiles. This figure illustrates the average share of misallocated payments across the FICO distribution for 100 equal-sized FICO buckets between 480 and 830. The graph is based on our sample of 34 million credit cards of borrowers who hold multple credit cards at the same bank in March 2019.

Electronic copy available at: https://ssrn.com/abstract=4126641

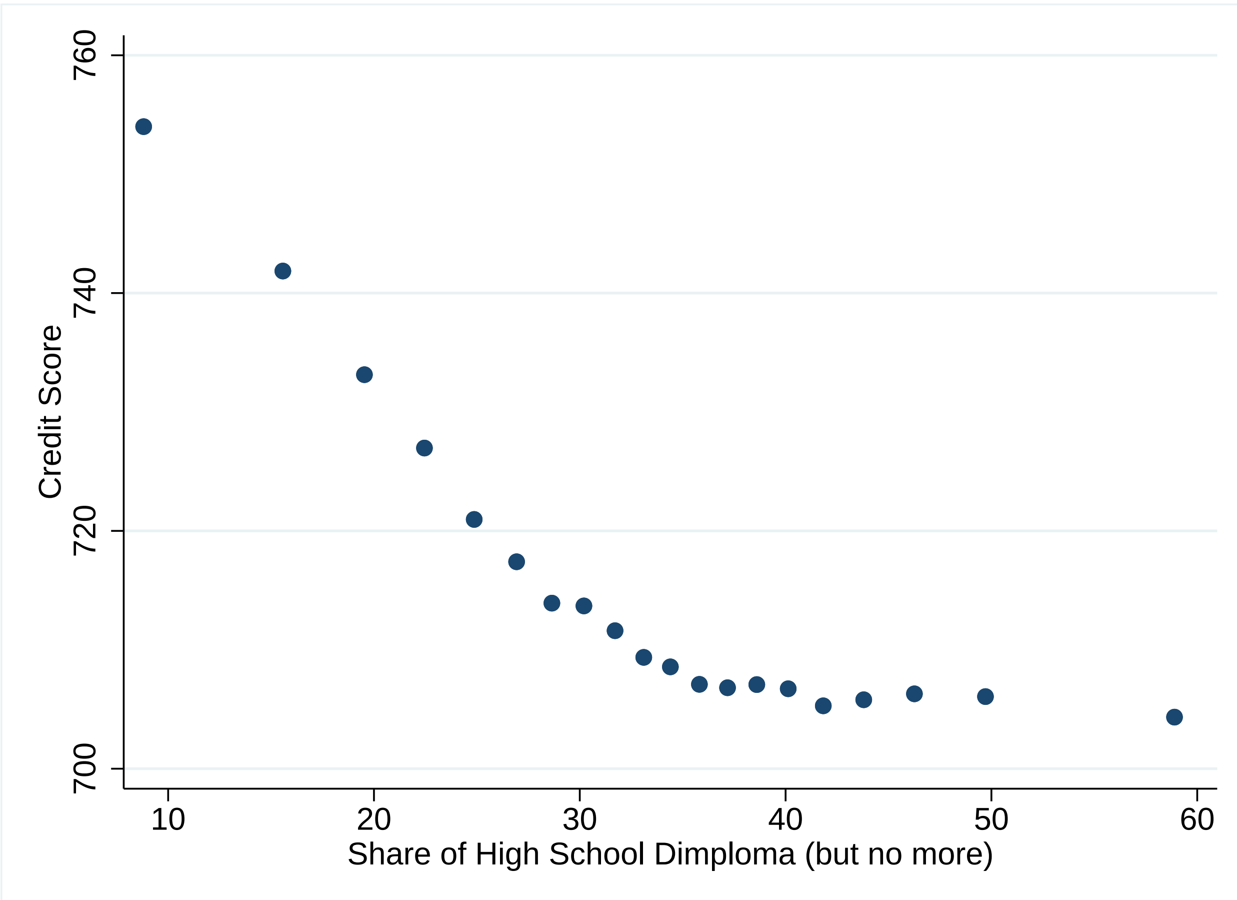


Figure 5. FICO Scores and Education. This figure provides a binned scatter plot and illustrates the bivariate relationship between average FICO scores and low educational attainment across 30,497 ZIP codes in the United States. Low educational attainment is measured by the percentage share of residents with a high school diploma but no more.

Electronic copy available at: https://ssrn.com/abstract=4126641

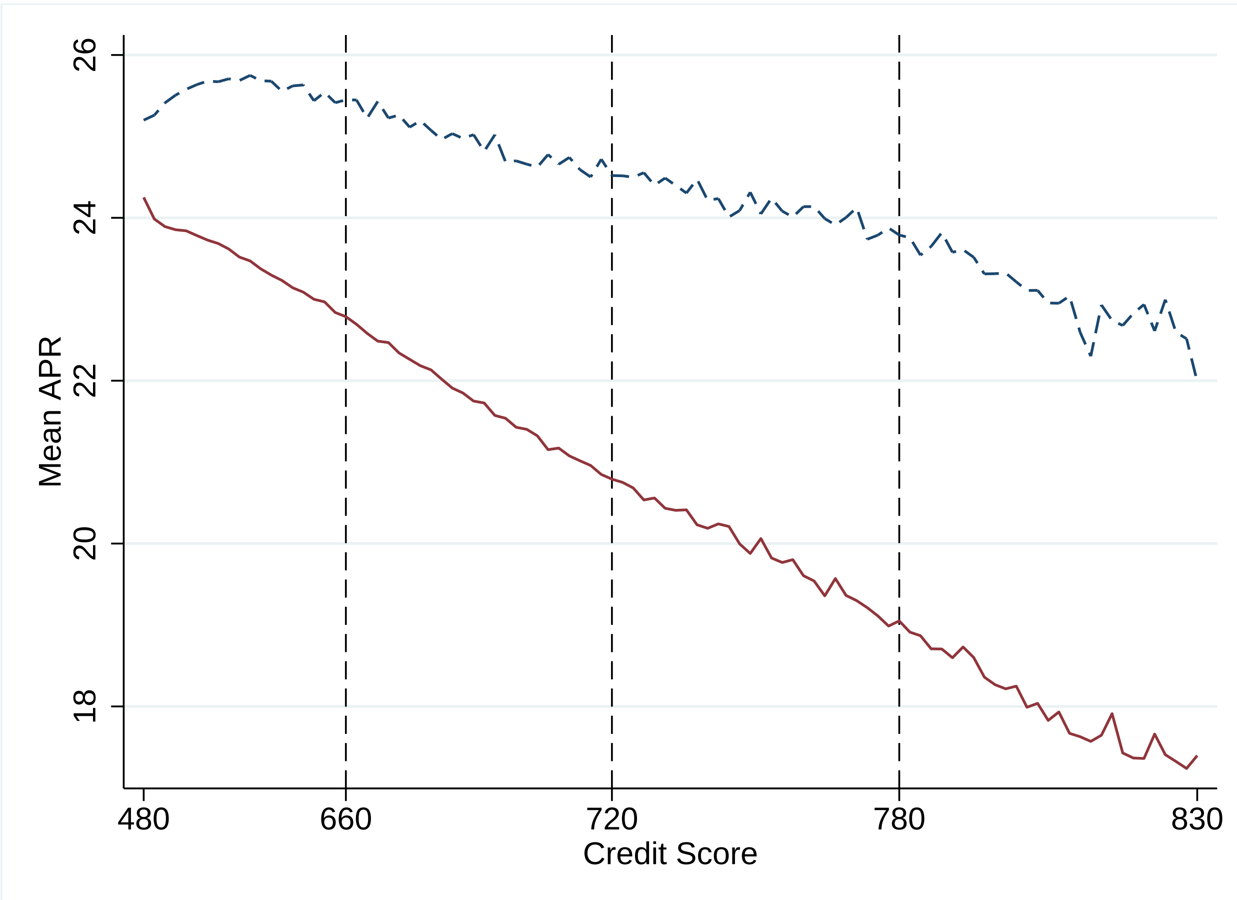


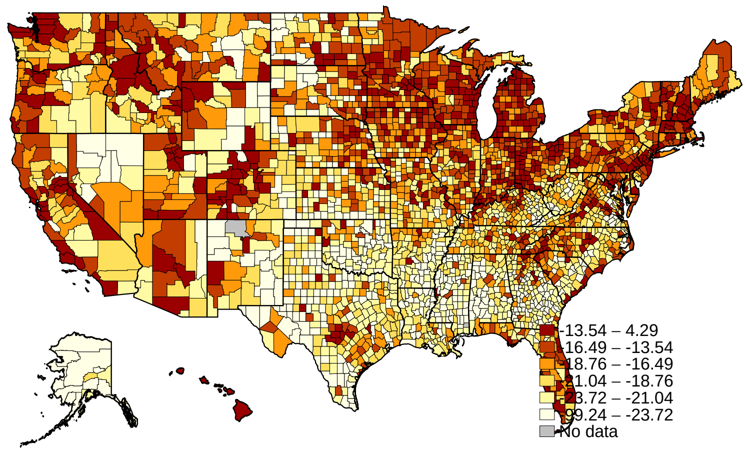
Figure 6. Annual Percentage Rates (APR) of Interest Across FICO Score Percentiles. This figure illustrates the average annual percentage rate (APR) of interest across the FICO distribution, separately for reward cards (solid red line) and classic cards (dashed blue line). For each card type, we plot 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 borrowers, respectively. The graph is based on our baseline sample of 166 million credit cards in March 2019.

Electronic copy available at: https://ssrn.com/abstract=4126641

Figure 7. Bank Revenue Shares Across FICO Score Percentiles. This figure illustrates the average bank revenue share per reward card across the FICO distribution for 100 equal-sized FICO buckets between 300 and 850. The figure illustrates the share of interchange income (black), fee income (dark gray), and interest income (light gray) as a percentage of total card revenue. The graph is based on our sample of 91 million reward cards in March 2019.

Electronic copy available at: https://ssrn.com/abstract=4126641

(A) Average Net Rewards Across Counties



(B) Average FICO Scores Across Counties

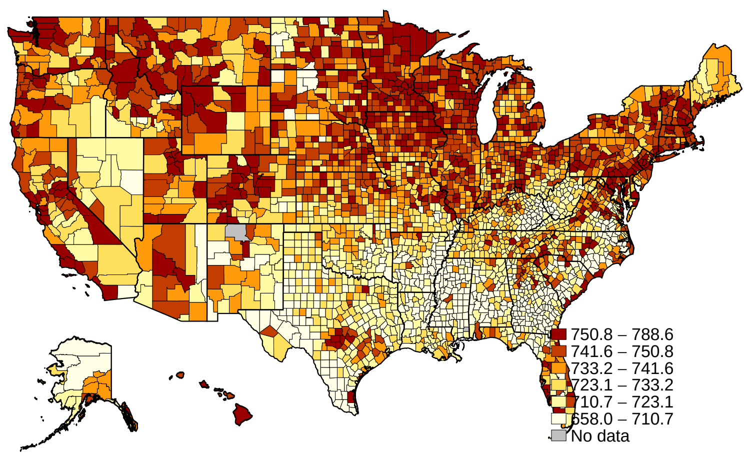


Figure 8. The Geography of Net Rewards and FICO Scores. This figure illustrates the average net rewards (Panel A) and average FICO score (Panel B) across counties in the United States. The graph is based on our baseline sample of 166 million credit cards in March 2019.

Electronic copy available at: https://ssrn.com/abstract=4126641

Electronic copy available at: https://ssrn.com/abstract=4126641

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), separately for reward and classic cards (Columns 4 and 5), and for the sample of borrowers with multiple cards within the same bank. Panel A presents variables related to net rewards (as described in Section IV.A) and credit scores. Panel B presents further credit card outcome variables. Panel C presents variables used as control variables in our regressions.

	All Cards			Reward	Classic	Multiple Card Sample
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Median	SD	Mean	Mean	Mean
Panel A. Net Reward Variables.						
Reward Card (0/1)	0.55	1.00	0.50	1.00	0.00	0.47
Gross Rewards (in $)	6.07	0.00	23.06	11.06	0.00	3.51
Interest Charges (in $)	17.80	0.00	41.28	20.84	14.09	21.17
Total Fee Charges(in $)	3.37	0.00	12.60	3.87	2.75	3.15
Net Rewards (in $)	−15.09	0.00	48.99	−13.65	−16.84	−20.81
Panel B. Other Credit Card Outcomes.						
Purchase Volume (in $)	478.14	8.74	1534.20	780.01	110.46	285.17
Outstanding Balances (in $)	1626.17	406.06	3100.10	2036.02	1117.83	
APR (in %)	21.99	22.24	5.02	19.87	24.57	22.63
Credit Limit (in $k)	7.76	5.00	8.12	10.58	4.33	6.21
Panel C. Control Variables.						
FICO Score	726.18	738.00	82.03	745.64	702.47	707.73
Borrower Income (in $k)	95.39	62.38	1666.68	109.56	78.13	90.73
Age of Card (in years)	6.42	4.00	6.85	6.53	6.30	6.79
Promotion Card (0/1)	0.12	0.00	0.32	0.09	0.15	0.13
Joint Account (0/1)	0.02	0.00	0.14	0.02	0.02	0.01
Deposit Relationship (0/1)	0.20	0.00	0.40	0.29	0.10	0.20
Lending Relationship (0/1)	0.08	0.00	0.27	0.10	0.05	0.08
No. Cards (same bank)	1.75	1.00	0.98	1.62	1.90	2.73
NPL share in Last 3 years	0.03	0.00	0.17	0.02	0.04	0.04
Observations	166,205,496	166,205,496	166,205,496	91,271,502	74,933,994	33,913,888

Electronic copy available at: https://ssrn.com/abstract=4126641

Table II

Net Rewards

This table presents the estimation results for differences in net rewards between reward cards and classic cards from Equations (5) and (6) in Section IV.B, where the outcome variable is the net reward of card i as defined in Equation (1) 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). We control for the following card characteristics (card age, promotion dummy, joint account dummy) and the following borrower characteristics (deposit relationship, lending relationship, number of cards, NPL in the last three years). Columns 1 to 4 use the full sample of cards and include the following fixed effects: bank (b), ZIP code (z), income percentile (w), FICO score percentile (f). Columns 5 and 6 uses the sample of borrowers with multiple cards at the same bank and include borrower fixed effects. Standard errors are clustered at the bank and state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

Table III

Aggregate Net Rewards

This table presents the aggregate sum of net rewards in million dollars for reward cards with negative and positive 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.

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

Electronic copy available at: https://ssrn.com/abstract=4126641

Electronic copy available at: https://ssrn.com/abstract=4126641

Table IV
Net Reward Components

This table presents the estimation results for differences in gross rewards, interest charges, and total fee charges between reward cards and classic cards from Equation (5) in Section IV.B:

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

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). We control for the following card characteristics (card age, promotion dummy, joint account dummy) and the following borrower characteristics (deposit relationship, lending relationship, number of cards, NPL in the last three years). All specifications include Bank (b) × ZIP Code (z) × Income Percentile (w) × FICO Score percentile (f) fixed effects. Standard errors are clustered at the bank and state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

Electronic copy available at: https://ssrn.com/abstract=4126641

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 (5) in Section IV.B:

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

We reports results separately for three different annual income groups: low (below $50,000), middle ($50-85,000), high (above $85,000). 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). We control for the following card characteristics (card age, promotion dummy, joint account dummy) and the following borrower characteristics (deposit relationship, lending relationship, number of cards, NPL in the last three years). All specifications include Bank (b) × ZIP Code (z) × Income Percentile (w) × FICO Score percentile (f) fixed effects. Standard errors are clustered at the bank and state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

Table VI
Credit Card Usage

This table presents the estimation results for differences in unpaid balances, purchase volumes, and credit card payments between reward cards and classic cards from Equation (5) in Section IV.B:

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

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). We control for the following card characteristics (card age, promotion dummy, joint account dummy) and the following borrower characteristics (deposit relationship, lending relationship, number of cards, NPL in the last three years). All specifications include Bank (b) × ZIP Code (z) × Income Percentile (w) × FICO Score percentile (f) fixed effects. Standard errors are clustered at the bank and state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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

Electronic copy available at: https://ssrn.com/abstract=4126641

Table VII

Share of Misallocated Payments

This table presents the estimation results for differences in the misallocated payment (MAP) share of between reward cards and classic cards from Equation (6) in Section IV.B:

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

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). We control for the following card characteristics (card age, promotion dummy, joint account dummy) and the following borrower characteristics (deposit relationship, lending relationship, number of cards, NPL in the last three years). We include the following fixed effects: ZIP code, bank, income percentiles, FICO score percentiles. Standard errors are clustered at the bank and state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Misallocated Payments	
	(1)	(2)
Reward Card	0.02***	
	(0.00)	
Reward Card × Sub-Prime		0.03***
		(0.00)
Reward Card × Near-Prime		0.02***
		(0.00)
Reward Card × Prime		0.01***
		(0.00)
Reward Card × Super-Prime		0.01***
		(0.00)
Card Controls	Y	Y
FE: Bank × Borrower	Y	Y
Observations	33,913,888	33,913,888
Mean Y	0.04	

Electronic copy available at: https://ssrn.com/abstract=4126641

Electronic copy available at: https://ssrn.com/abstract=4126641

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

This table presents the estimation results for differences in annual percentage rates (APR) and bank profits between reward cards and classic cards from Equation (5) in Section IV.B:

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

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). We control for the following card characteristics (card age, promotion dummy, joint account dummy) and the following borrower characteristics (deposit relationship, lending relationship, number of cards, NPL in the last three years). We include the following fixed effects: ZIP code, bank, income percentiles, FICO score percentiles. Standard errors are clustered at the bank and state level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	APR		Profit	
	(1)	(2)	(3)	(4)
Reward Card	-1.87^{***}		4.05^{***}	
	(0.27)		(0.62)	
Reward Card × Sub-Prime		-0.76^{***}		-3.19^{***}
		(0.14)		(1.01)
Reward Card × Near-Prime		-1.62^{***}		14.60^{***}
		(0.30)		(1.17)
Reward Card × Prime		-2.54^{***}		6.15^{***}
		(0.34)		(0.55)
Reward Card × Super-Prime		-2.70^{***}		-0.56^{***}
		(0.32)		(0.38)
Card Controls	Y	Y	Y	Y
Borrower Controls	Y	Y	Y	Y
FE: Bank × ZIP × Income × FICO	Y	Y	Y	Y
Observations	166,205,496	166,205,496	166,205,496	166,205,496
Mean Y	21.99		19.43	

Table IX
The Geography of Net Rewards

This table presents the estimation results for net rewards at the ZIP code-level from Equation (10) in Section VIII:

$$\text{Net Reward}_{i,z} = \sum_k \beta^k X_z^k + \varepsilon_{i,z}$$

where 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 high school diploma (but no more) as a proxy measure for education, the median income of individuals in the ZIP code, the population density per square kilometer, 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)
Low Education	-0.39^{***}			
	(0.04)			
Household Income (in $k)		0.12^{***}		
		(0.01)		
Population Density			0.10^{***}	
			(0.04)	
Black Population Share				-0.16^{***}
				(0.01)
Observations	166,205,496	166,205,496	166,205,496	166,205,496
Adjusted R^2	0.39	0.01	0.35	0.19

Electronic copy available at: https://ssrn.com/abstract=4126641

Online Appendix

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

May 2022

Electronic copy available at: https://ssrn.com/abstract=4126641

A. Credit Card Clustering

Table A1

This table reports the detailed categories used for credit card clustering at the individual product level in the calculation of net rewards in Section IV.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

Electronic copy available at: https://ssrn.com/abstract=4126641